Claude Shannon Versus Gus Archie: Information Theory as a Guide to Log Evaluation Without Petrophysics*

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Abstract

Around 1950 Gus Archie, working at Shell Oil, changed petroleum exploration by developing a theoretical foundation for e-log interpretation based on certain electrical properties of rocks. From this discipline of petrophysics, Archie's Equation is universally used and needs no introduction. At about the same time Claude Shannon, working at Bell Labs, changed communication by developing a mathematical structure for messaging. Oversimplifying the explanation here, information theory uses the received signal to assess if data have changed the probability that some predictable outcome is valid. Verification of the expected outcome is redundant and provides no new information. New data add information only if they change the weight of evidence to suggest that an unexpected event (a surprise) has occurred. For information theory, the message itself is understood only to be a choice between possible alternatives; the actual meaning of the message is not relevant.

This paper proposes that the principles of information theory provide a suitable framework for a "theory-less" evaluation of triple-combo log data by identifying unexpected or anomalous pairings in key log parameters. Further, geologic interpretations derived from these anomalies generate significant results for exploration in shale resource plays.

Examples of key cross-plot pairs (independent variable -v- dependent variable) from log data will be shown: (1) shale (clay) volume -v- average neutron-density porosity and (2) average neutron-density porosity (log scale) -v- resistivity (log scale). Where the dependent variable is predictable from the independent variable (typically a linear trend), redundancy dominates and no significant information is present. In contrast, an anomalous positive deviation of the dependent variable from the

predictable baseline trend signals "surprising" information and the probability is quantifiable based on the amount of deviation. From these plots, we can make geologic interpretations concerning (1) effective porosity (PHIE) in the shales and (2) hydrocarbon charge (HCSAT).

In this way, the meaning of the message is separated from the probability that it is valid. Pay zones can be identified on the logs and mapped based on the coincidence of a high probability for effective porosity and hydrocarbon saturation. Finally, inferences on pore structure and reservoir deliverability can be developed by using the PHIE and HCSAT parameters in a meta-data analysis.

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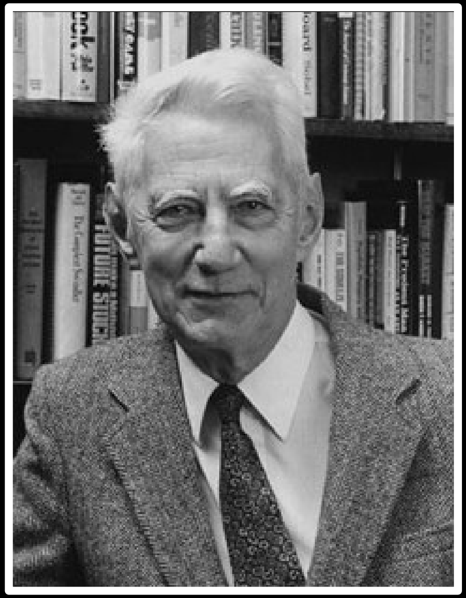
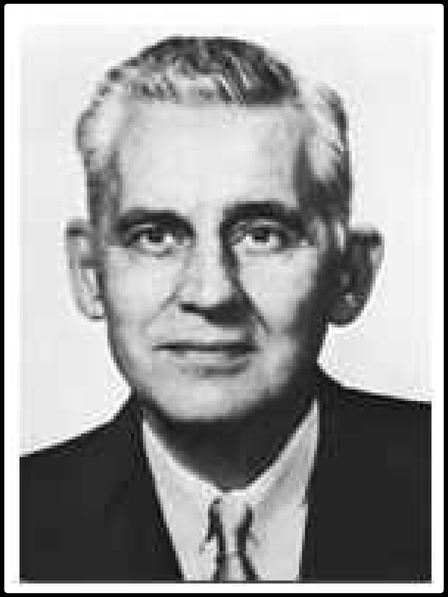
CLAUDE SHANNON -vs- GUS ARCHIE





Information Theory as a Guide to Log Evaluation without Petrophysics

Paul E. Devine, WPX Energy

WPXENERGY

RMS-AAPG – DENVER, CO – JULY 22, 2014

CLAUDE SHANNON -vs- GUS ARCHIE

Information Theory as a Guide to Log Evaluation without Petrophysics

- This presentation covers a log evaluation method I have been using for about 5 years to look at unconventional reservoirs - mainly shales. Just last year I first read about Claude Shannon and some ideas from Information Theory. I was struck by just how well certain principles supported my techniques and possibly explained why I can produce what I think are successful results from a fairly simple process. This is what I would like to share with you today.

- ***NOTE***: *Maps that were shown during the session at the RMS-AAPG in Denver, 2014, were released by WPX Energy for presentation only. Because these maps were not released for publication, certain displays that appeared in the original have been modified or deleted for the current production.*

WHAT'S AHEAD

TALK ORGANIZATION	EXPLORATION APPROACH
PREMISES of the EVALUATION METHOD	SIMPLE - EMPIRICAL - PRAGMATIC
METHOD SETUP and CALCULATIONS	PROBABLY APPROXIMATELY CORRECT
EXAMPLE RESULTS	UNIQUELY COMPETITIVE ANSWER

WHAT'S AHEAD

- Here's what's ahead. I will start by describing premises of the method. Then I will move to a discussion of the actual calculations. And finally, I will end with some examples.
- Each of these topics has a corollary that relates to my approach toward any exploration project. First, I want the concepts to be simple, empirical and pragmatic; second, I want the results of my process to be probably approximately correct (this has a formal definition that will be described in an appendix slide if you are interested); and third, I want my answers to provide unique opportunities for action (I want to see things that others have missed).

GUS ARCHIE: PETROPHYSICS

BULLETIN OF THE AMERICAN ASSOCIATION OF PETROLEUM GEOLOGISTS
VOL. 34, NO. 5 (MAY, 1950), PP. 943-961, 13 FIGS.

INTRODUCTION TO PETROPHYSICS OF RESERVOIR ROCKS[1]

G. E. ARCHIE[2]
Houston, Texas

DETERMINISTIC
BASED ON MEASURED PARAMETERS

ARCHIE'S EQUATION

FORMATION WATER RESISTIVITY

TORTUOSITY FACTOR

WATER SATURATION

SATURATION EXPONENT

$$Sw = \left[\frac{R_w}{R_t} \times \frac{a}{\phi^m} \right]^{\frac{1}{n}}$$

CEMENTATION EXPONENT

FORMATION RESISTIVITY

POROSITY

MODIFIED FROM:
Dan Krygowski
The Discovery Group, Inc.

DEFINING THE TERMS

GUS ARCHIE: PETROPHYSICS

- In the late 1940s/early 1950s Gus Archie, working at Shell Oil, found a need for formal evaluation of reservoir rocks, focusing mainly on the response of porosity, resistivity and water saturation in well logs. Petrophysics was born. Archie's equation shown here is the most iconic expression of petrophysics and you can see by the formula that this work set the future course of petrophysics as a deterministic discipline.

CLAUDE SHANNON: INFORMATION THEORY

The Bell System Technical Journal

Vol. XXVII | July, 1948 | No. 3

A Mathematical Theory of Communication

By C. E. SHANNON

PROBABILISTIC

BASED ON DATA STRUCTURE

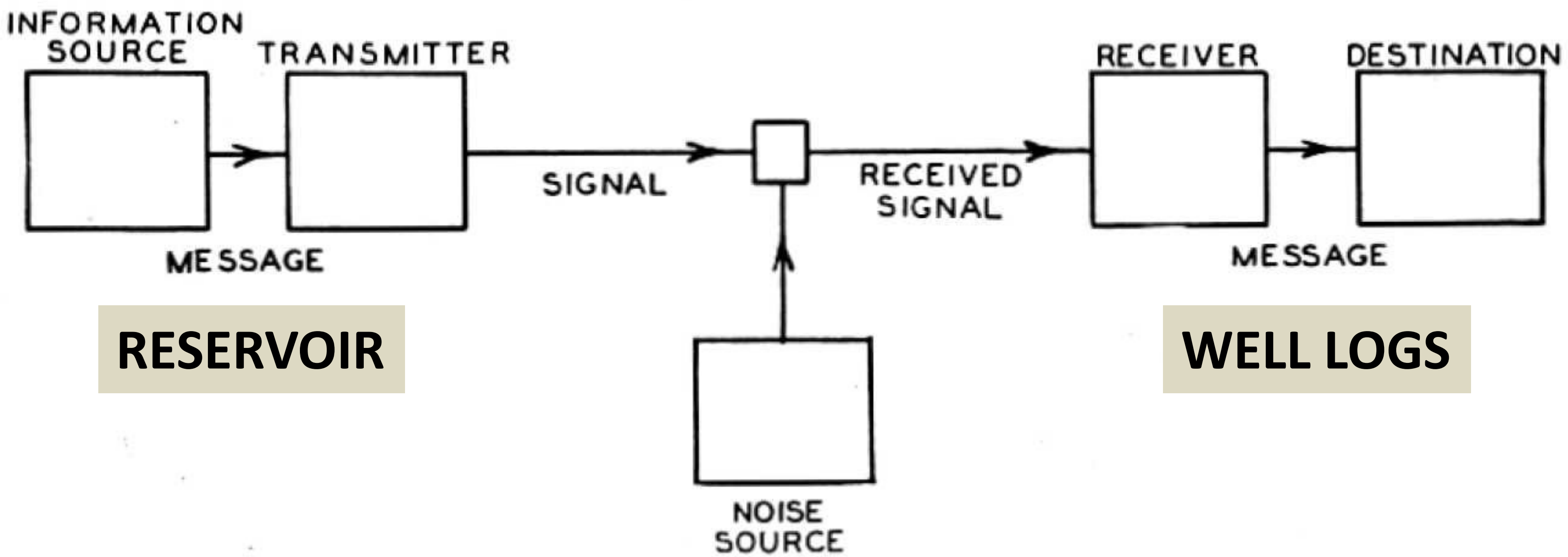
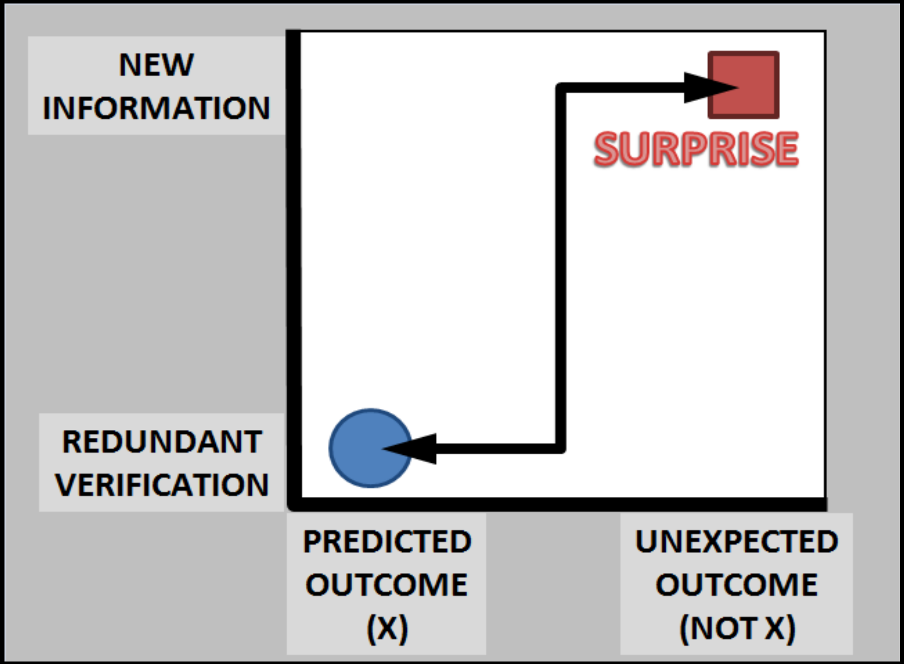


Fig. 1—Schematic diagram of a general communication system.

CLAUDE SHANNON: INFORMATION THEORY

- At about the same time, Claude Shannon was working at Bell Labs and attempting to develop a mathematical structure of communication. He saw the problem as one of receiving information at one place that was generated at another yet transmitted through a noisy system. Based on his work as a codebreaker in WWII - where an infinite number of potential messages was possible - his answers had to be probabilistic. If we consider our reservoir to be the source of a message and well logs as the receiver – we see that Archie and Shannon were really in the same business.

INFORMATION THEORY (1)



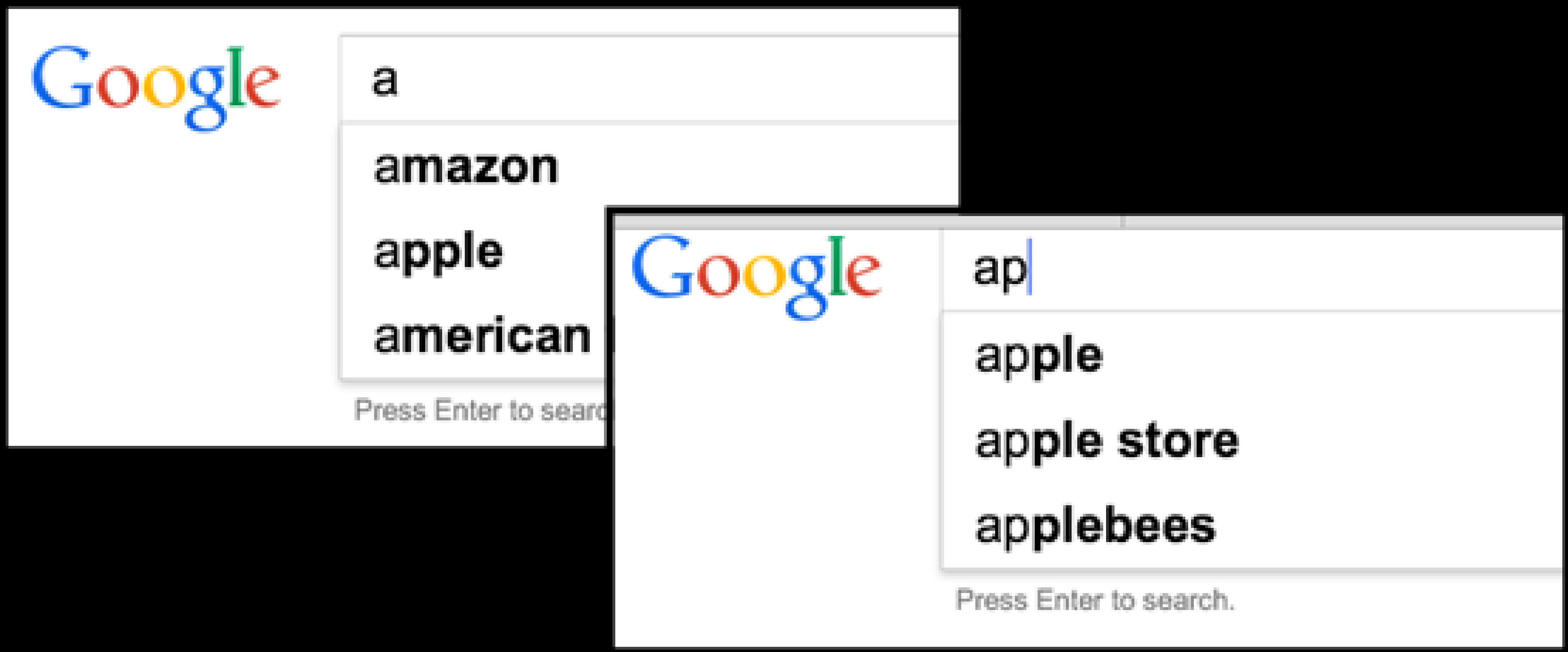
- **Information theory uses the received signal to assess if new data have changed the probability that some predictable outcome is valid.**

- Verification of the expected outcome is redundant and provides no new information.
- New data add information only if they change the weight of evidence to suggest that an unexpected event (a surprise) has occurred.
- For information theory, the message itself is understood only to be a choice between possible alternatives; the actual meaning of the message is not relevant.

INFORMATION THEORY (1)

- Let's start with a little explanation of information theory – at least what I understand as the important points. Information Theory uses the received signal to assess if new data have changed the probability that some predictable outcome is valid - verification of the expected outcome provides no new information; only data that bring a surprise carry new information.
- For example – here we have a predicted outcome – in this case a blue circle – and if the new data verify the expected result, they are redundant and carry no new information. I predict X and I get X. If however we get an unexpected result that is NOT X – here, a red square – then new information is present. This surprise is the hallmark of new information. Finally – the concept only concerns itself with the choice among alternatives (I am going to get either a predicted result or a surprise result), the meaning of the message is not relevant in determining information content.

INFORMATION THEORY (2)



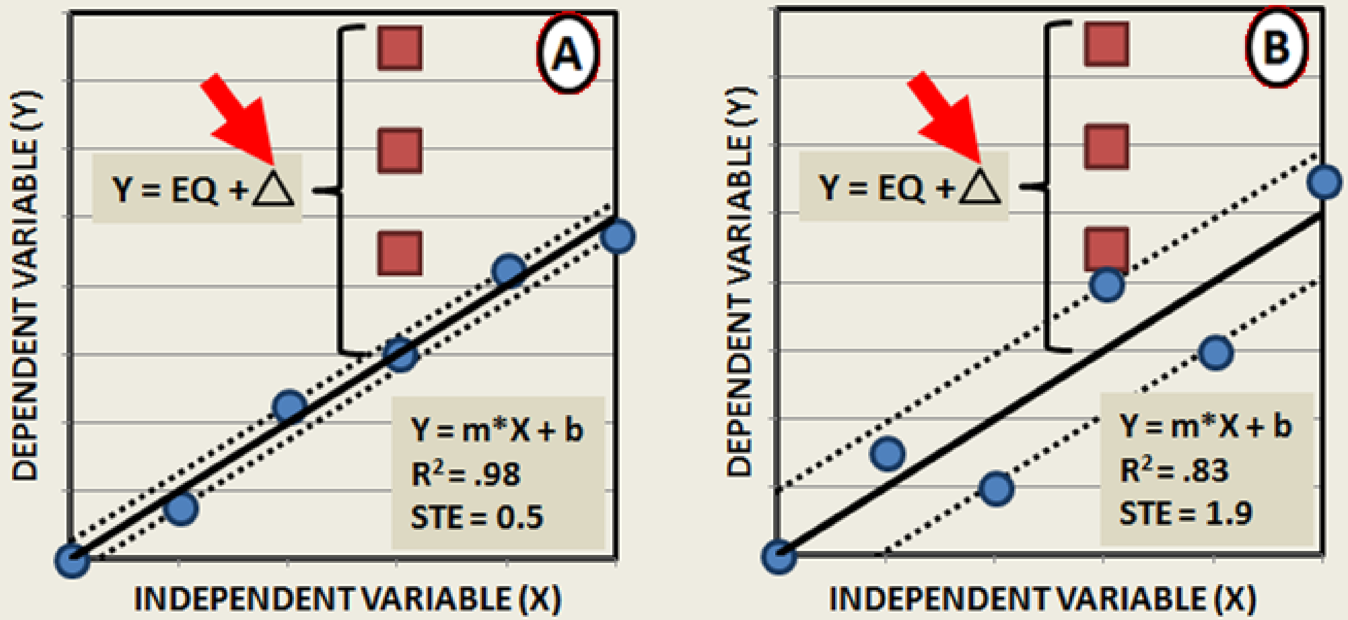
GOOGLE SEARCH EXAMPLE

INFORMATION THEORY (2)

- Here, I have a simple case using a GOOGLE search example to compare verification and surprise in information theory. If I type the letter “A”…the GOOGLE search predicts that I am looking for AMAZON. If I am indeed searching for AMAZON, the letters -MAZON simply verify GOOGLE’s prediction; they are redundant and typing these letters into the search will provide no new information. If however I am searching for APPLE, additional information is required for an accurate prediction. And if I am looking for APPALACHIAN, then considerably more information will apparently be needed.

INFORMATION THEORY (3)

- **Application to data cross-plots**



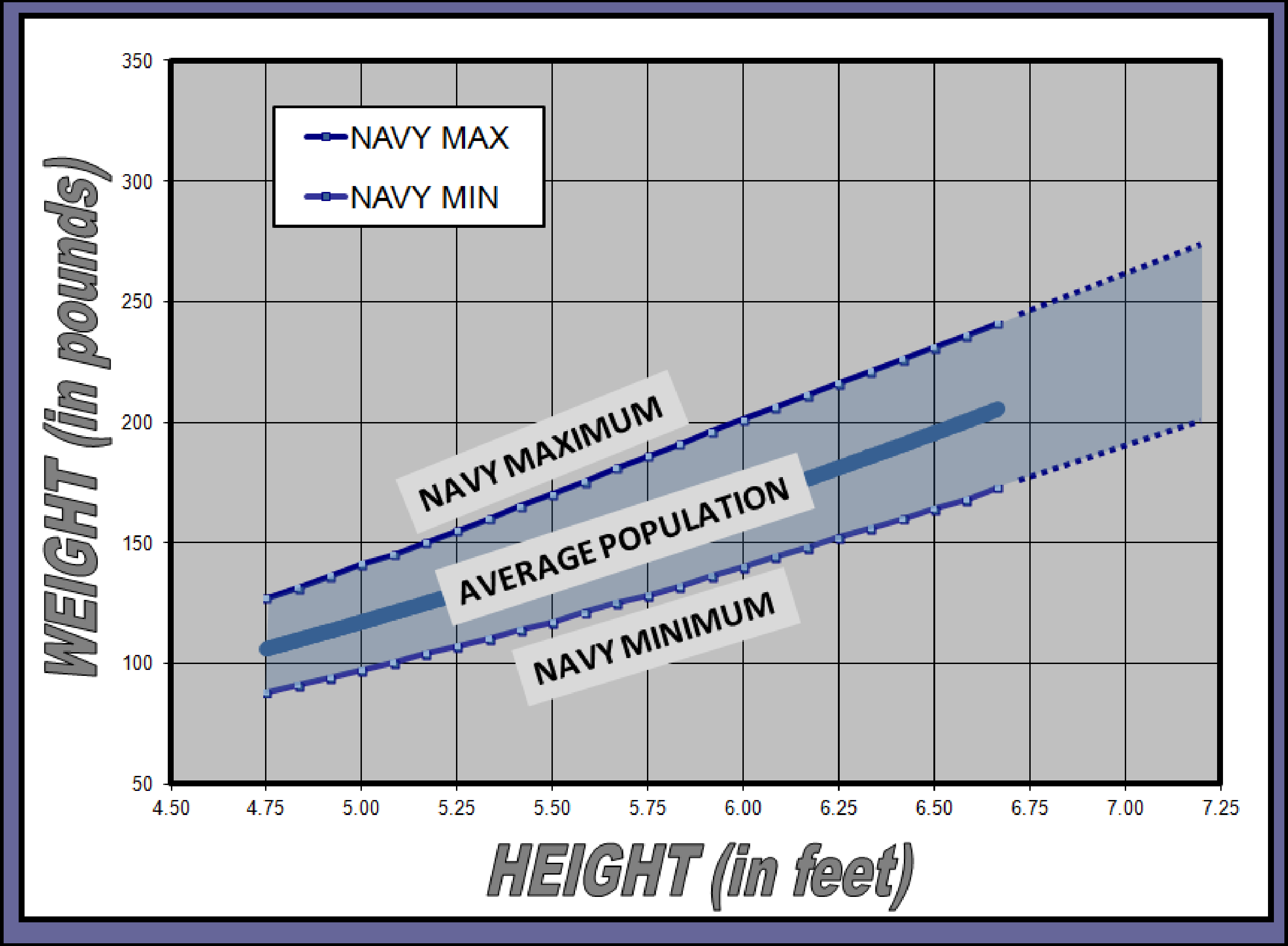
The equation Y=m*X measures the predictability of "Y_{TREND}" based on changes in variable X

The parameter "△" is a measure of SURPRISE, indicating an increasing probability of "not Y_{TREND}".

INFORMATION THEORY (3)

- The method I am going to show today uses data cross-plots to determine if our received signal indicates verification or surprise.
- In “A” -on the left- the equation for the blue trendline predicts a “y-trend” value from any x input. Here, any data that fall along the trendline offer only redundant verification – but the red squares here do provide new information and the distance from the trendline is a measure of surprise. This distance quantifies the probability that these anomalous data are not part of the “y-trend” and therefore contain new information.
- In “B” -on the right- we see that the more uncertain we are about the “y-trend” relationship – the more uncertain we will be about our surprise as the trend results begin to overlap the anomalies. Next we will look at an example of surprise from a cross-plot of real-world data to more fully develop the concept.

ANOMALOUS DATA REPRESENT NEW INFORMATION (1)

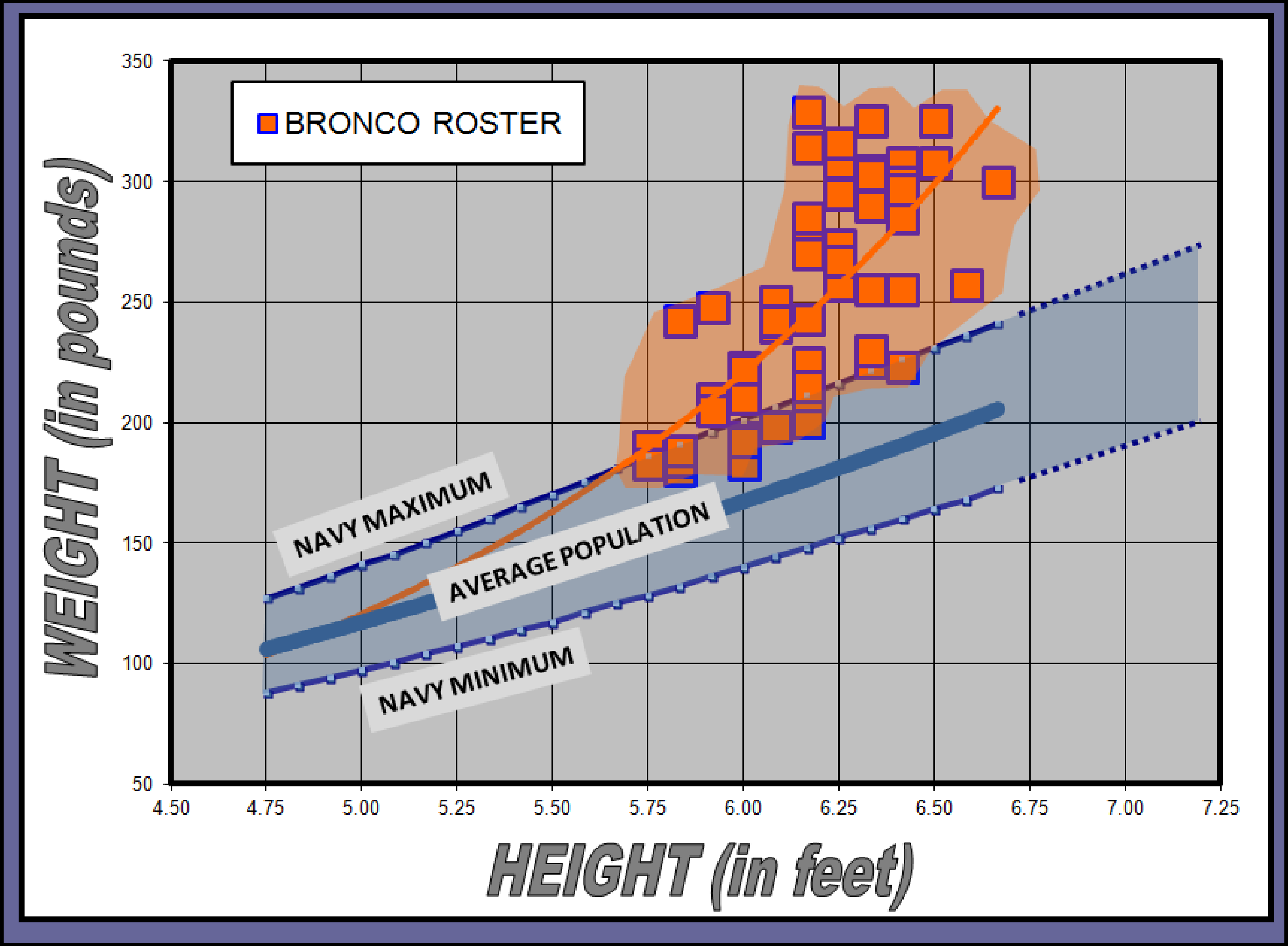


- Population Height – Weight Example

ANOMALOUS DATA REPRESENT NEW INFORMATION (1)

- Here we have a plot showing the US Navy's trend of acceptable height (x-axis) versus weight (y-axis) for its sailors which we can assume represents a trend for the general population. A recruit needs to fit into this trend to do the work involved in operating a modern warship.

ANOMALOUS DATA REPRESENT NEW INFORMATION (2)

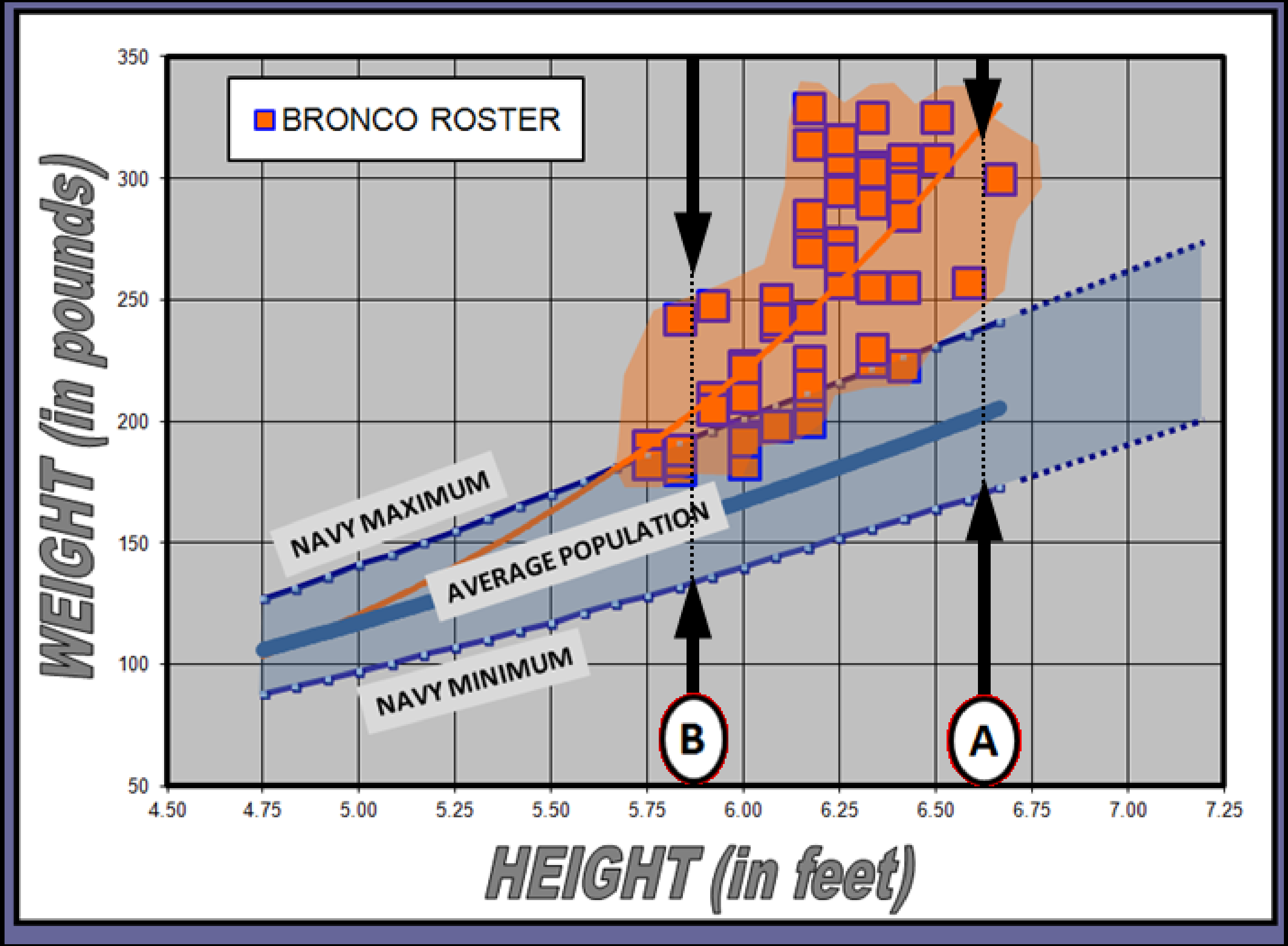


- Population Height-Weight Example
- **SURPRISE!** associated with the Broncos data

ANOMALOUS DATA REPRESENT NEW INFORMATION (2)

- If we add the height-versus-weight data from the Denver Broncos football team we see a different distribution. These are not really extreme individuals; extreme data would fall at the ends of the trend by definition. Data from the Broncos are more properly characterized as anomalous types; and, if you saw some 6-foot-5, 300-pound dude in your doorway, I dare say you would experience considerable surprise. Anomalies produce surprise, extremes do not. Further, you could use the characteristics from the trend of the average population as a filter to identify candidates for the NFL. The height-weight data of each individual will be generally successful in predicting members of the general population who will never play in the NFL. But not always.

ANOMALOUS DATA REPRESENT NEW INFORMATION (3)

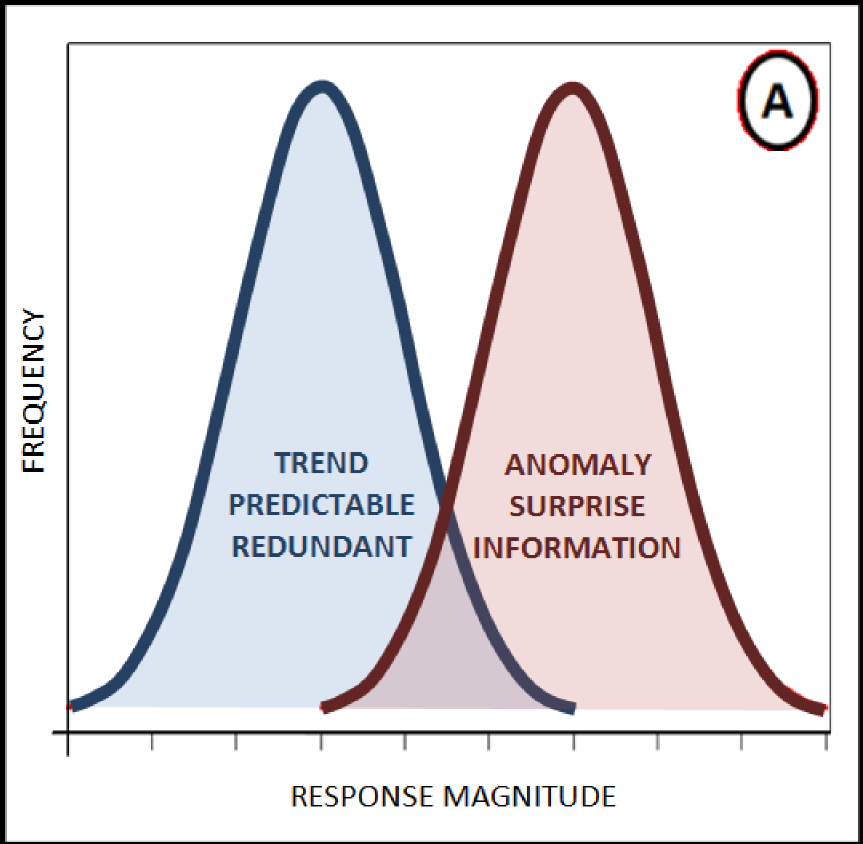


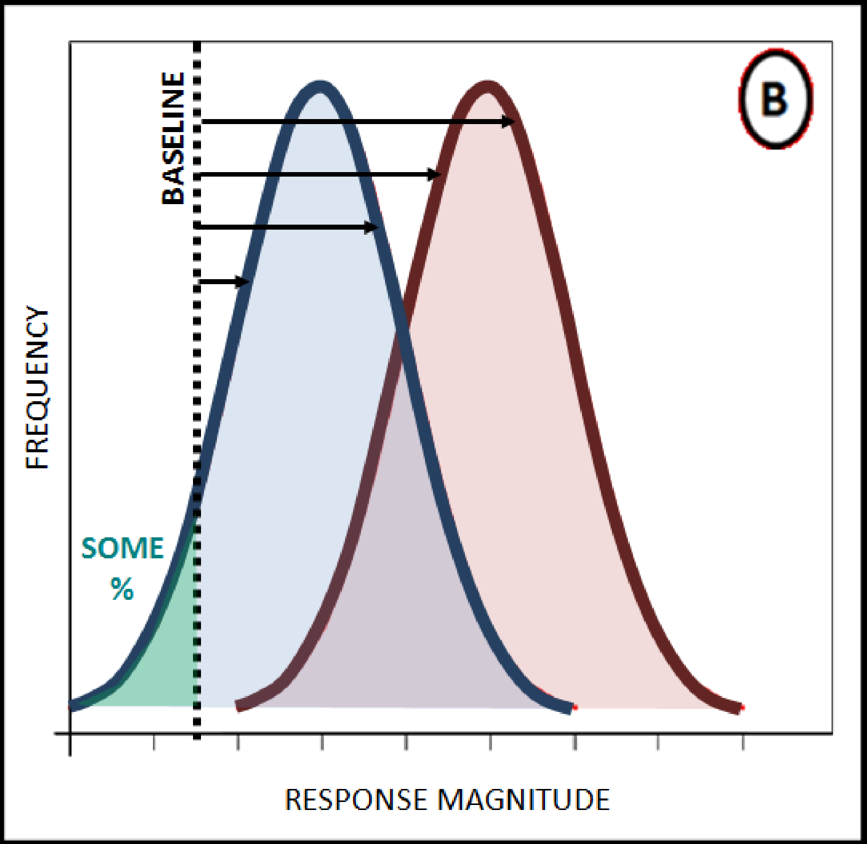
- Population Height-Weight Example
- **SURPRISE!** associated with the Broncos data

ANOMALOUS DATA REPRESENT NEW INFORMATION (3)

- I will end this discussion by looking at two sections (A and B) through the data. Note that at “A” there is a discrete separation between the trend and the anomalous data; whereas at “B”, the distributions show significant overlap.

DATA MEASUREMENTS





Trend Data and Anomalous Data may be discrete and easily identified.
More often data form a continuum between trend and anomaly.

Distance from the BASELINE provides a measure of the PROBABILITY that the data are part of the Predictable Trend or constitute a SURPRISE!

The BASELINE is essentially a filter

DATA MEASUREMENTS

- These images show the same concept from the previous slide but here we are looking at a cross-section of the data distributions. In “A”, the predictable trend is well separated from the surprise data and we would have no problem recognizing either distribution. In “B”, however, I am showing a large amount of overlap between the two distributions which is much more realistic for the actual well-log data we’ll be evaluating.
- Here, I don't have a way to identify a regression for the trend distribution, so I need a slightly different solution. I instead draw a baseline somewhere in the low-response data and use that as the source of measurements. In this way I can still quantify the probability that I am either in the trend data --with low numbers-- or in surprise data --with high numbers. Ultimately, the baseline acts as a filter that separates verification from surprise.

FILTERING NOISE FROM SIGNAL

Potential errors in signal/noise detection are well known:

ANOMALY DETECTION	ANOMALOUS DATA	
	PRESENT	ABSENT
IDENTIFY A SURPRISE	HIT	FALSE ALARM
EVALUATION		
IDENTIFY ONLY THE PREDICTABLE DATA TREND	MISS	CORRECT ANALYSIS

FILTERING NOISE FROM SIGNAL

- Finally, we have to be aware of the limitations of the method. Two potential errors in signal detection based on data filtering are well known. (1) If we identify a surprise event in noisy data but this event is actually part of the trend, we have a false alarm or false positive. (2) And we can miss information in data from the minimal tail of the anomalous distribution where they overlap a wide (noisy) trend. Thus we are again reminded that the data analysis based on Information Theory is probabilistic, not deterministic.

WELL LOG DATA: INFORMATION FILTERS

EAGLE FORD WELL EXAMPLE

POROSITY FILTER

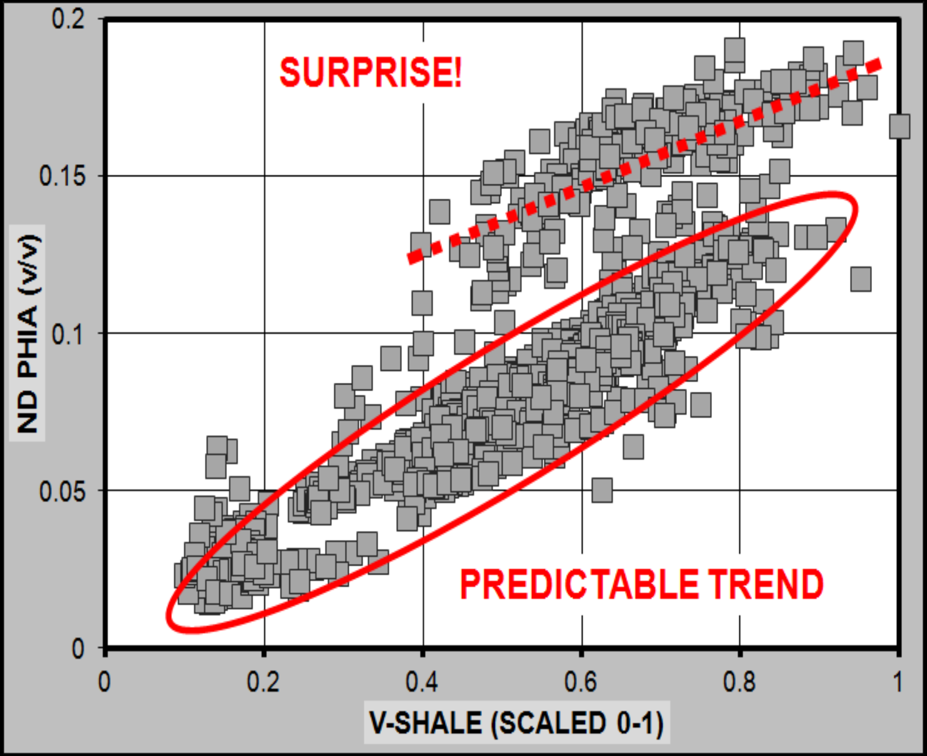
V-SHALE -vs- ND PHIA

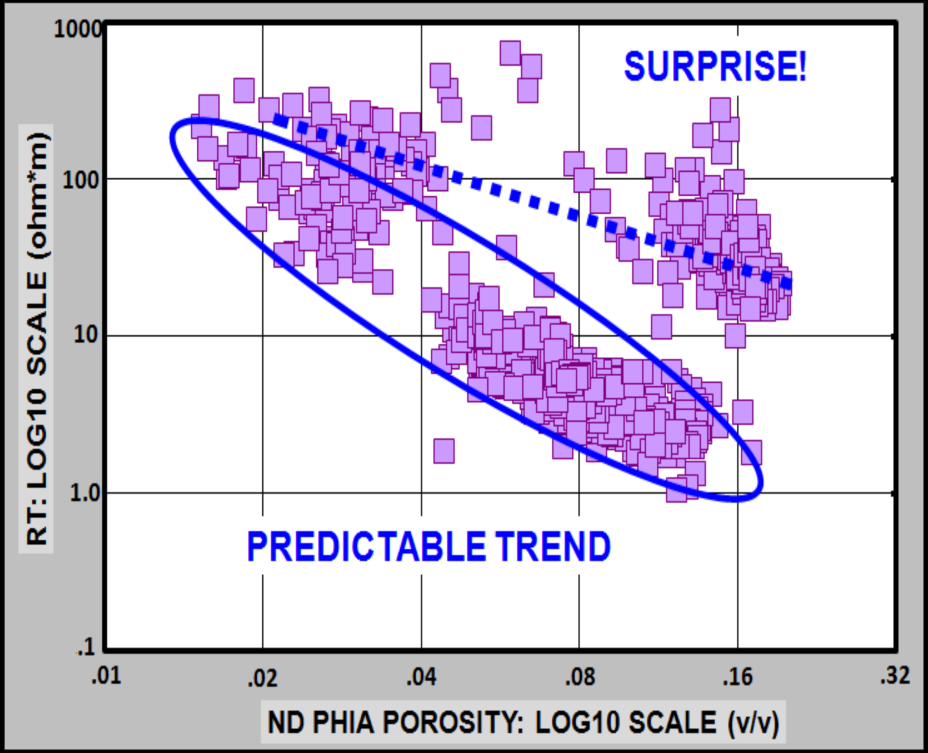
Does shaliness predict total porosity?

RESISTIVITY FILTER

ND PHIA -vs- RESISTIVITY

Does total porosity predict resistivity?





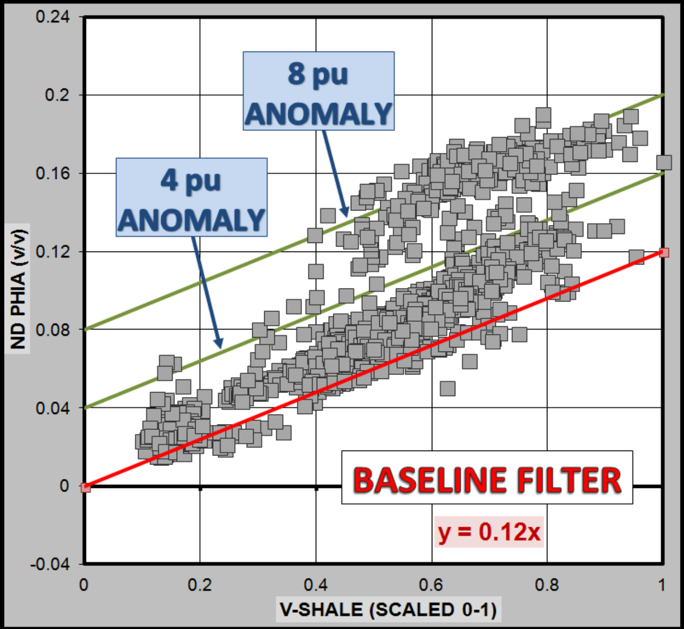
WELL LOG DATA: INFORMATION FILTERS

- So now we turn to geologic data from well logs. Data here are from a well in the Eagle Ford Shale play of SE Texas.
- On the left I have a cross-plot of v-shale versus porosity. The question I want the porosity filter to address is: Does shaliness predict porosity? If so, data in that trend have no information content. In this case there is a very obvious discrimination between the predictable trend that relates shaliness to porosity and a second surprise trend.
- The plot on the right shows porosity versus resistivity both with log10 scales to keep the trends looking linear. Here I want the resistivity filter to ask: Does porosity predict resistivity? If so -again- there is no information content. As before we have a pretty obvious separation of trend and surprise data.

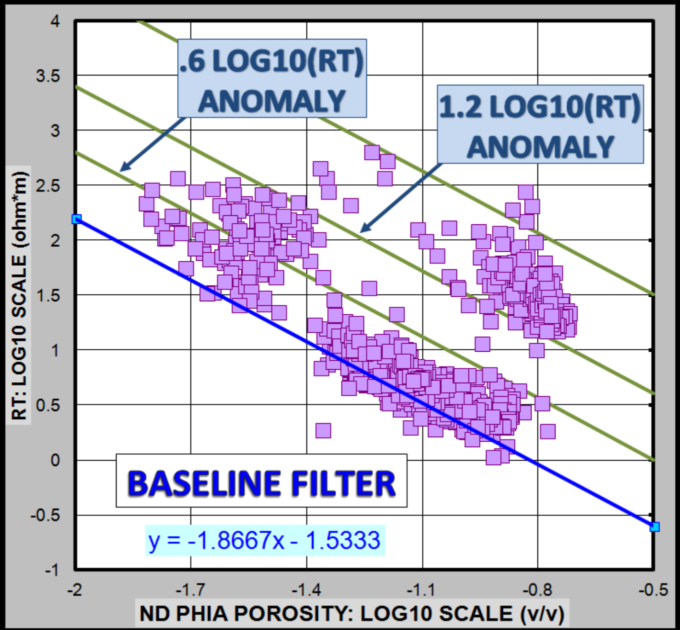
WELL LOG DATA: INFORMATION CONTENT ONLY

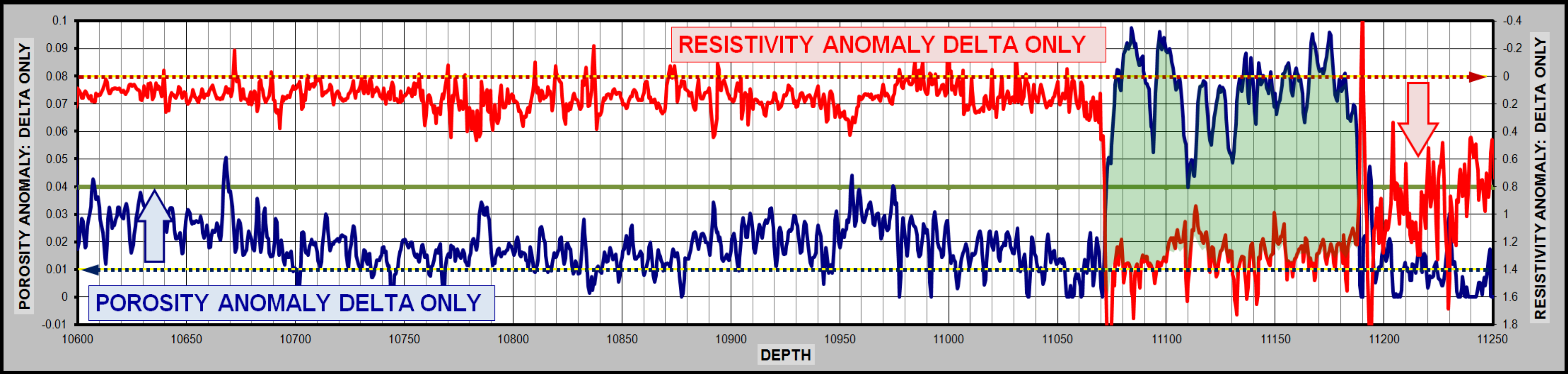
EAGLE FORD WELL EXAMPLE

POROSITY ANOMALY
V-SHALE versus TOTAL POROSITY FILTER



RESISTIVITY ANOMALY
TOTAL POROSITY versus RESISTIVITY FILTER



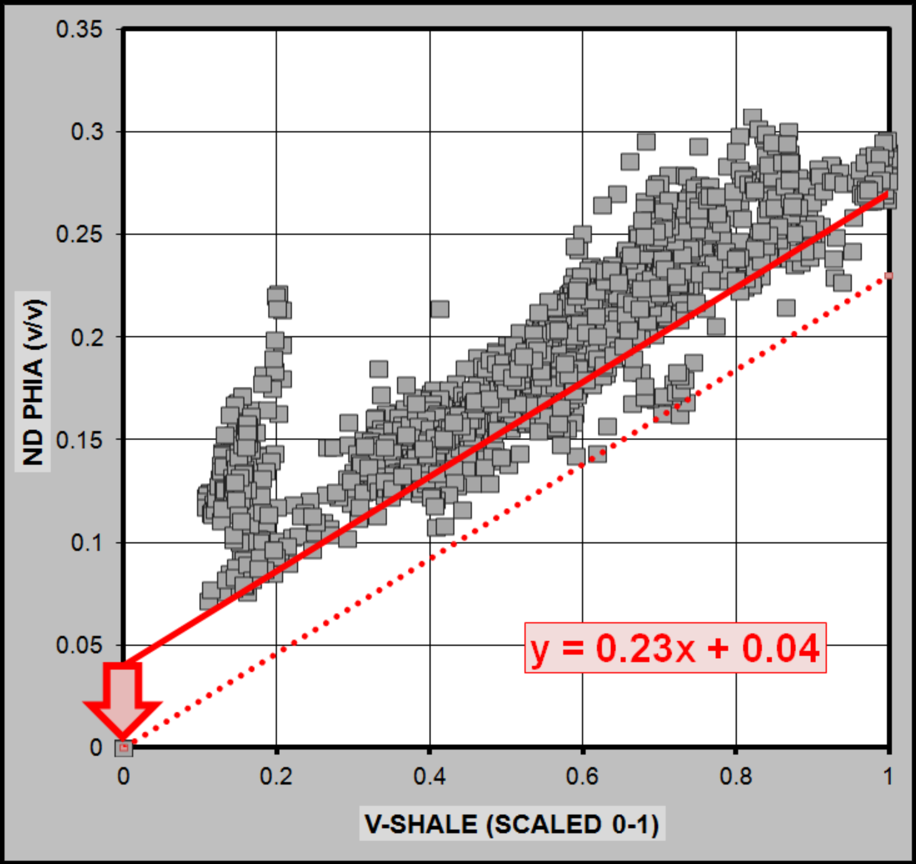


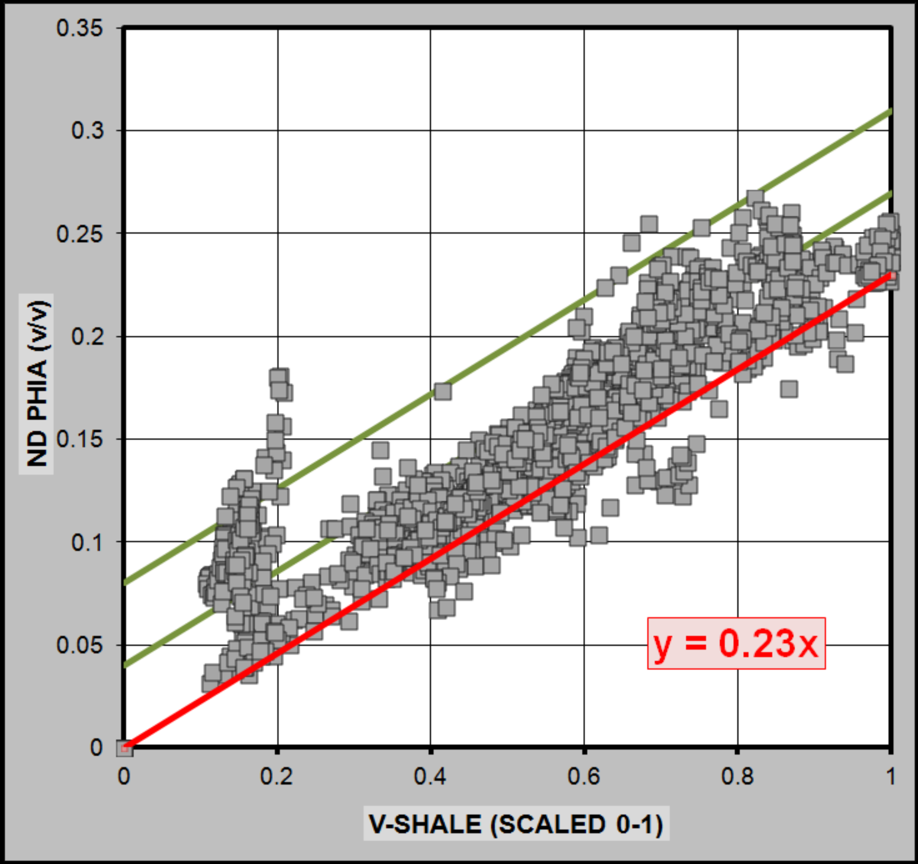
WELL LOG DATA: INFORMATION CONTENT ONLY

- Next, I am now showing the two previous cross-plots with baseline filters drawn in the low-response data. I have also drawn lines of equal distance from the baseline to quantify surprise. The probable information content increases with distance from the baseline filter.
- In the log display below I have the porosity-anomaly calculations (in blue) scaled on the left – and increasing upward; the calculation for the resistivity anomaly (in red) is scaled on the right and increases downward. Coincidence of the two anomalies is colored green where the two curves cross. Of course the anomalous porosity and resistivity interval here comes from the prolific shale reservoirs of the Eagle Ford.
- Congratulations, you have found your first unconventional target by simply quantifying the information content of the data. At this point I only identified where we received information; I made no attempt <u>yet</u> at interpreting a meaning for the message. The other examples I have for you today are from the Niobrara of the DJ Basin and nothing there will be quite so obvious. And of course we <u>do</u> want to try to interpret the messages contained in that information. Let's go there next.

POROSITY ANOMALY: INTERPRETATION

NIOBRARA WELL EXAMPLE, DJ BASIN





(1) BASELINE FILTER SET WITH A SMALL (6.5%) PERCENTAGE OF THE DATA BELOW THE TREND

(2) DATA SHIFTED TO NORMALIZE THE BASELINE FILTER TREND AT THE CROSS-PLOT ORIGIN (0,0)

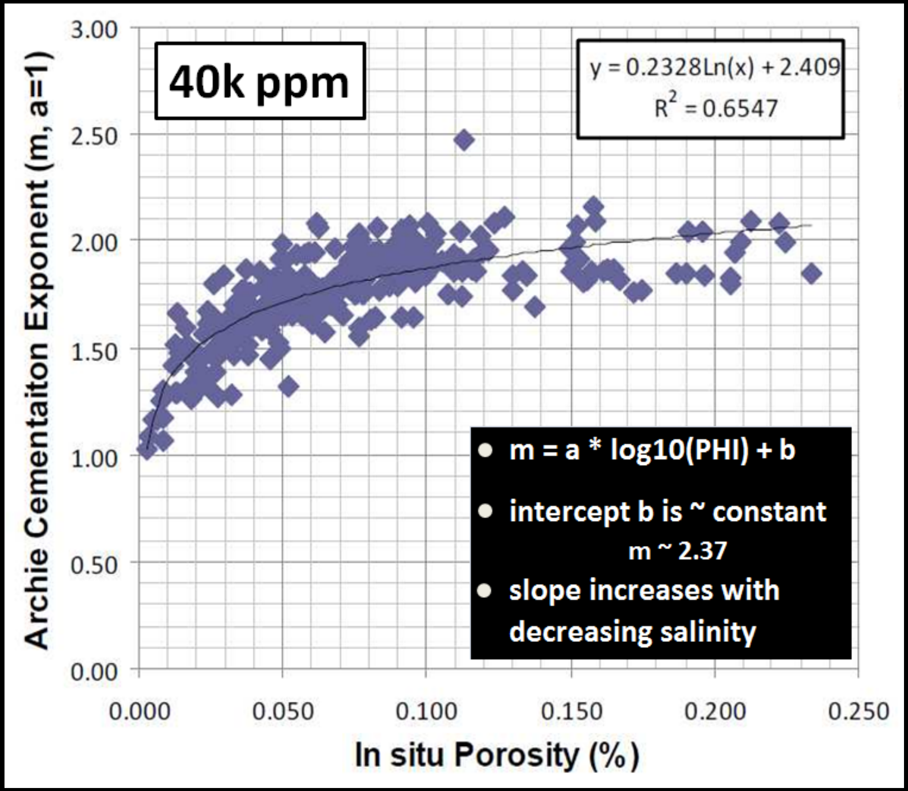
> Porosity Anomaly: > Probability of PHIE

POROSITY ANOMALY: INTERPRETATION

- First we will take a look at the setup for the porosity anomaly. This filter is trying to remove the effect of clay content on the total ND porosity measured by the logs. If you can predict porosity based on shale content, that's not a porosity you want – no matter what the magnitude. The baseline filter is drawn with some small percentage of the data below the trend.
- You will notice in the first plot on the left -in the raw data- that the baseline intersects the porosity axis some 4 units above the origin. I always bulk shift the total porosity data so that the baseline passes through the origin. This is a reasonable step for porosity normalization since by definition the porosity contributed by clay should be zero when the clay content is zero.
- Now I’m in a position to interpret the message identified by the porosity filter: a greater distance from the baseline represents a larger porosity anomaly. A larger porosity anomaly indicates a higher probability that the reservoir is transmitting a signal for effective porosity (PHIE) not influenced by clay content.

RESISTIVITY ANOMALY: INTERPRETATION (1)

Archie Parameters: Effect of a variable “m”



DATA REQUIRED FOR ACCURATE DETERMINISTIC "m"

MATRIX DENSITY

WATER SALINITY

35% OF SOMETHING ELSE

SOURCE: Cluff et al., RMS-AAPG, 2008

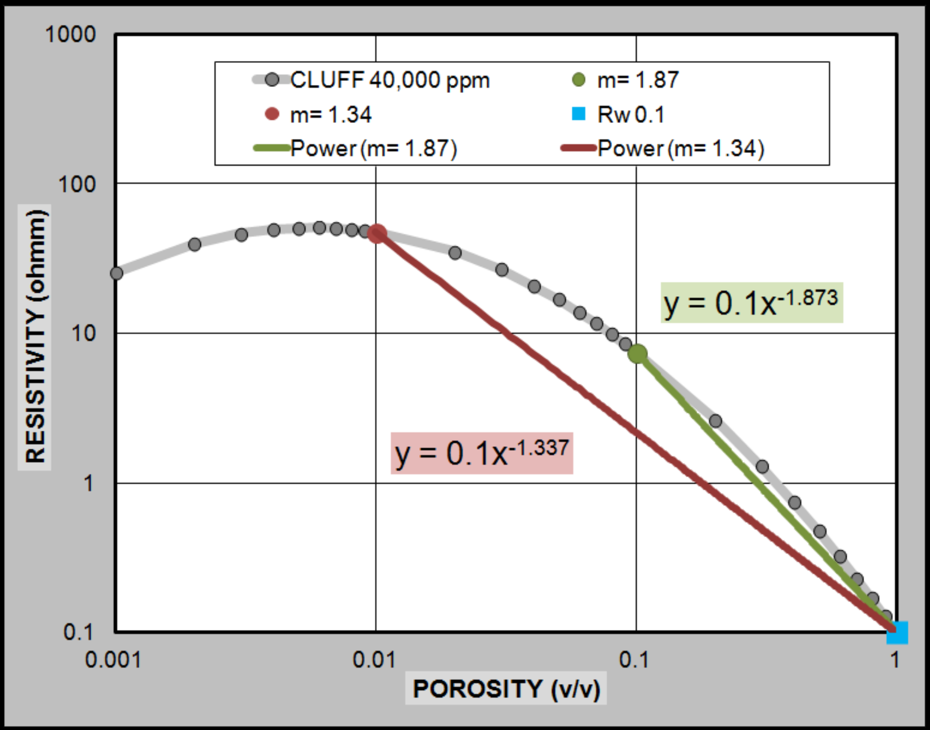
The effect of a variable "m" in a porosity-resistivity cross-plot is to produce a curved trend of wet resistivity (Ro).

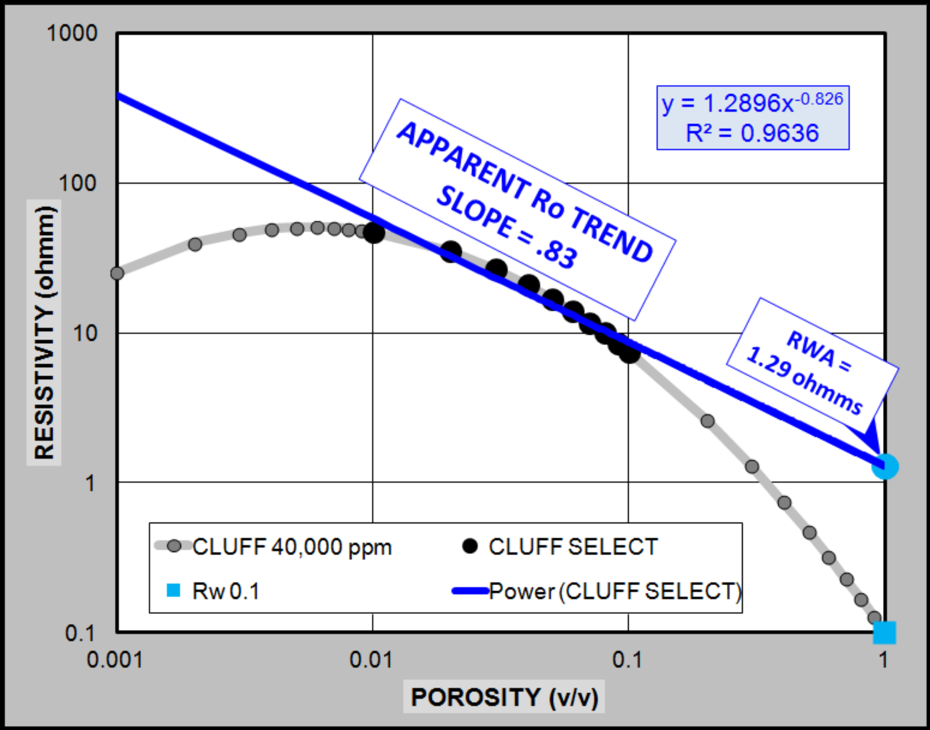
RESISTIVITY ANOMALY: INTERPRETATION (1)

- Next we turn to the resistivity anomaly. One of the most interesting developments in petrophysics in the past 10 years or so has been the work by Alan Byrnes, Bob Cluff, and others showing that the Archie exponent “m” is not constant but varies with relation to reservoir porosity. Of course the work shown here was for Mesaverde tight sands, but I believe this principle --of variable “m”-- applies to all reservoirs…we just don’t know what equations to use. I think this presents a *serious* challenge for the deterministic efforts at log evaluation -especially in exploration- while at the same time…I believe this opens the door for a probabilistic approach. So, the important point here becomes…what effect does a variable “m” have on a porosity-resistivity cross-plot? The result turns out to be a curved shape to the wet resistivity trend – Ro.

RESISTIVITY ANOMALY: INTERPRETATION (2)

40,000 ppm @ 125 degF, Rw=.1 ohmms





Reason for the curved Ro trend

Consequences of the curved Ro trend

NOTE: For predictive applications, the porosity-resistivity cross-plot requires proper positioning of the variables .

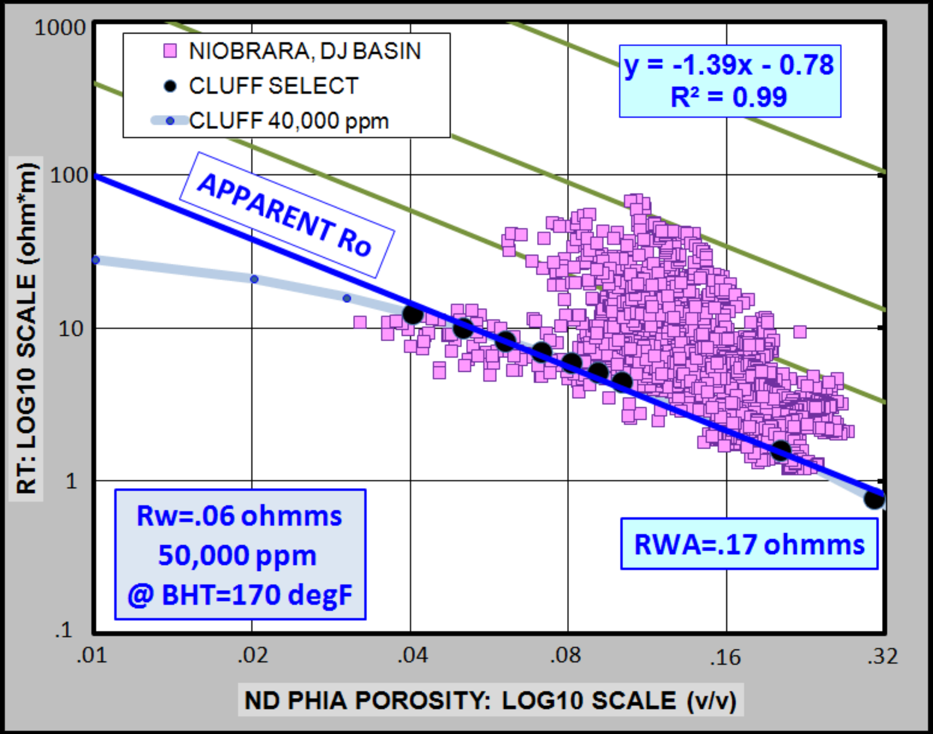
- ❑ Porosity is the independent variable and should be located on the x-axis
- ❑ Resistivity is the dependent variable and should be located on the y-axis

RESISTIVITY ANOMALY: INTERPRETATION (2)

- Here we have an example of the curved Ro trend produced by Cluff's equation from the previous slide. You can see -on the left- why this curve happens. The slope of “m” to each point on the Ro trend becomes progressively lower as porosity decreases. Examples at 10% and 1% porosity are shown. But if I'm looking for a flat baseline filter over a reasonable porosity range this actually causes no problems -as shown on the right.
- I can create a viable analysis by using a tangent to the curve as long as I also use the minimum RWA projected by the line and not what I supposedly “know” is the actual Rw. Note that the slope of the apparent Ro trend here is .83, a value which is way outside any range a traditional petrophysicist would accept; but it is 100% correct on an empirical/pragmatic basis.
- <u>*NOTE*</u>*: For a predictive application like this, the variables need to be properly positioned. Porosity is the independent variable and needs to be on the x-axis; resistivity is the dependent variable and should be located on the y-axis. So please…no more Mr. Pickett.*

RESISTIVITY ANOMALY: INTERPRETATION (3)

NIOBRARA WELL, DJ BASIN



for HC Saturation:
apply the saturation exponent "n"

RWA RATIO = 10 ^ (RES ANOMALY)

HC SAT = 1 - ((1 / RWA RATIO) ^ .5)

(1) Baseline filter captures minimum RWA trend of dataset

(2) Baseline filter is tangent to the variable "m" Ro trend

(3) True for any reasonable range of porosity

> Resistivity Anomaly: > Probability of HCSAT

RESISTIVITY ANOMALY: INTERPRETATION (3)

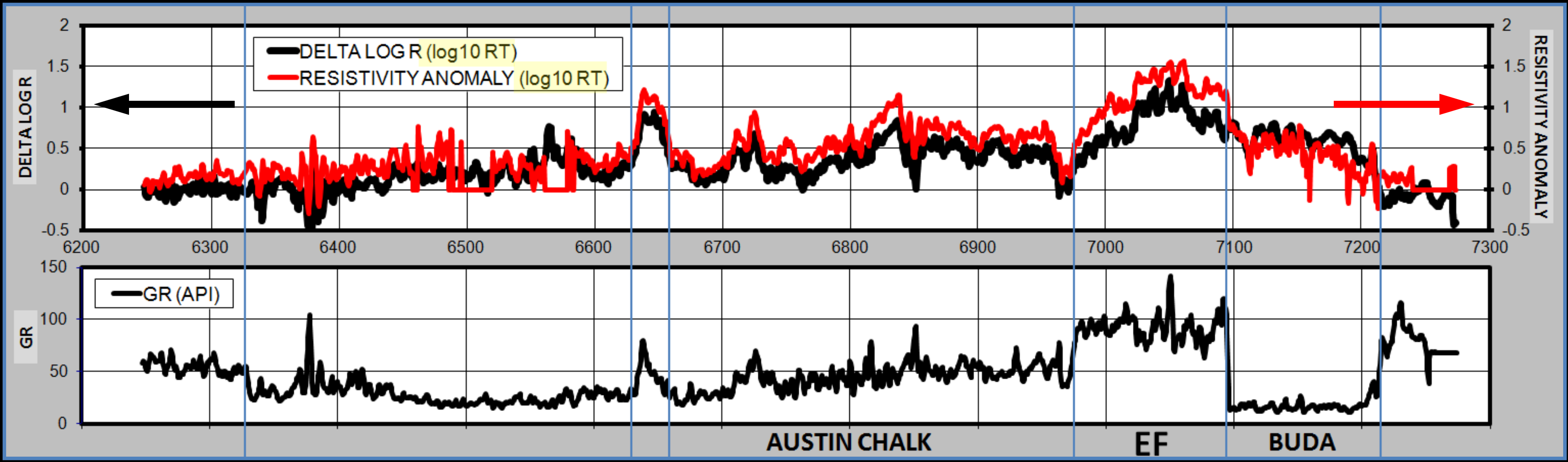
- Here is the last image for the resistivity anomaly setup with some actual Niobrara well log data covering a range of maybe more than 16 porosity units. The idea is: If you can predict resistivity from porosity you don't want that rock; in fact, Archie informs us that this is most likely a wet reservoir. Note that the flat baseline I've drawn is both tangent to the variable "m" trend and…at the same time…captures the minimum RWA of the data set (slope= 1.39 and RWA= .17 ohmms).
- In summary: these concepts have shown that I can produce almost exactly the same analysis as the deterministic approach by just using the internal structure of the data. I don't have to know anything else. In step 1, I quantify the surprise data using the baseline filter. And now, in a second step, I can produce an interpretation of the message by converting the resistivity anomaly to an RWA ratio and applying the saturation exponent. The resulting interpretation is this: the greater the resistivity anomaly – the greater the probability that the reservoir is signaling HC saturation.

Isn't this just a Pickett plot?

No – this is a two-step process:

(1) Calculate the resistivity anomaly based on distance from the baseline

(2) Interpret the anomaly with a second algorithm designed to assess the probability of a specific, desired condition (HCSAT or something else)



for HC Saturation:
apply the saturation exponent "n"

RWA RATIO = 10 ^ (RES ANOMALY)

HC SAT = 1 - ((1 / RWA RATIO) ^ .5)

for Organic Content:
compensate for thermal maturity (LOM)

TOC = ΔlogR x 10 ^ (2.297 - 1.0688 x LOM)

source: Passey et al., AAPG Bulletin (1990)

- For information theory, the message itself is understood only to be a choice between possible alternatives; the actual meaning of the message is not relevant.

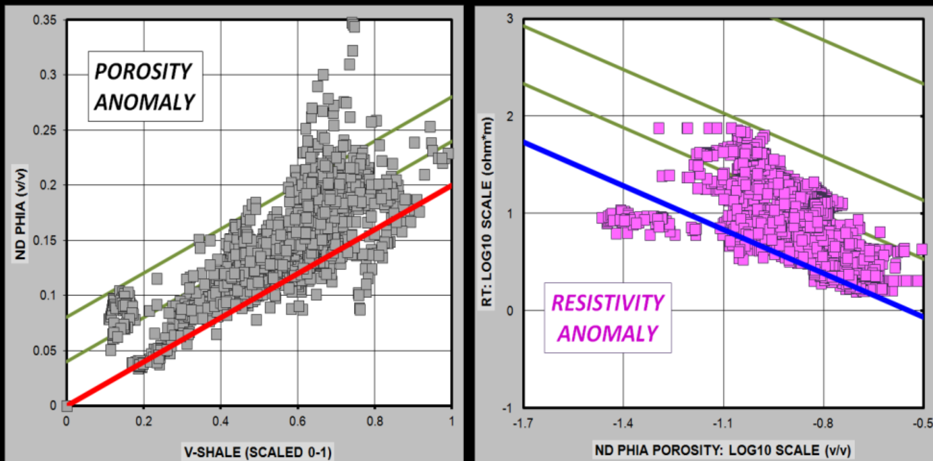
Isn't this just a Pickett plot?

- Many of you might be thinking…sure, you changed the axes…but, but you're interpreting HC saturation from porosity and resistivity…so, isn't this really just a Pickett plot? The simple answer is no. For example, in unconventional resource-play assessment, a resistivity anomaly can have another, professionally acceptable interpretation: as an indicator of organic content. Consider Passey's 1990 method commonly referred to as *delta-log-R*. We are instructed to graphically position a sonic DT curve (with linear scale) against a resistivity curve (with log10 scale) and identify zones where DT doesn't overlay log10(RT). This is just a caveman way of looking for resistivity anomalies. Baseline data occur where the two curves coincide: DT predicts log10(RT) and *delta-log-R*=0. Surprise information occurs where the curves diverge: *delta-log-R*>0.
- The slide shows data from the Eagle Ford play with two curves plotted against depth. The *delta-log-R* calculation is shown in black (scale to the left) with my resistivity anomaly in red (scale to the right). The units for both curves are in log10(RT) and the data are practically identical. The message, *delta-log-R,* actually has no unique meaning. Organic content can only be quantified from the *delta-log-R* message by applying a second algorithm to compensate for thermal maturity (LOM) as directed in Passey's article. Or, HC saturation can be estimated by converting the resistivity anomaly to a RWA ratio and applying the saturation exponent. It's a subtle point captured here by Information Theory: anomalous data only assess the signal for surprise to determine if there is new information which suggests a change in probability that something unexpected has occurred. The message truly does require a second interpretation for it to have a geologic meaning.
- Be sure to think about this the next time someone comes into your shop and proudly presents a *delta-log-R* anomaly without the LOM correction. What is the true meaning of this anomaly…organic content or HC saturation?

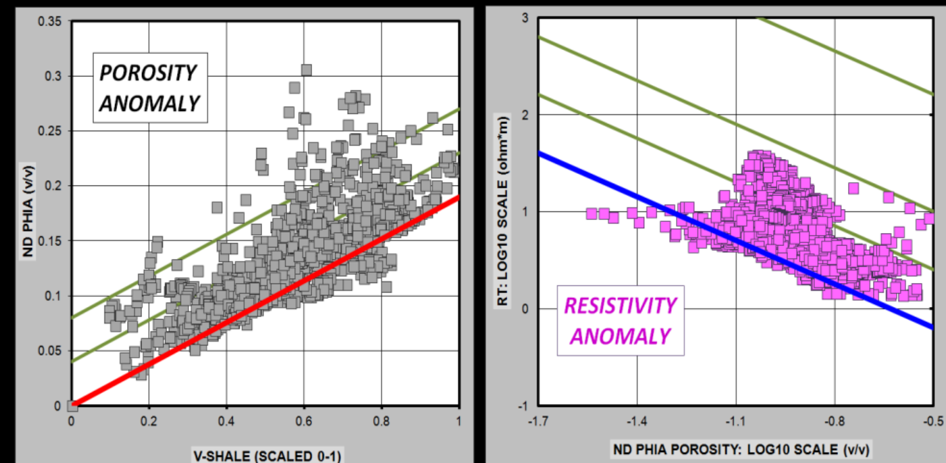
BASELINE / ANOMALY COMPARISONS

POROSITY BASELINE IS RED

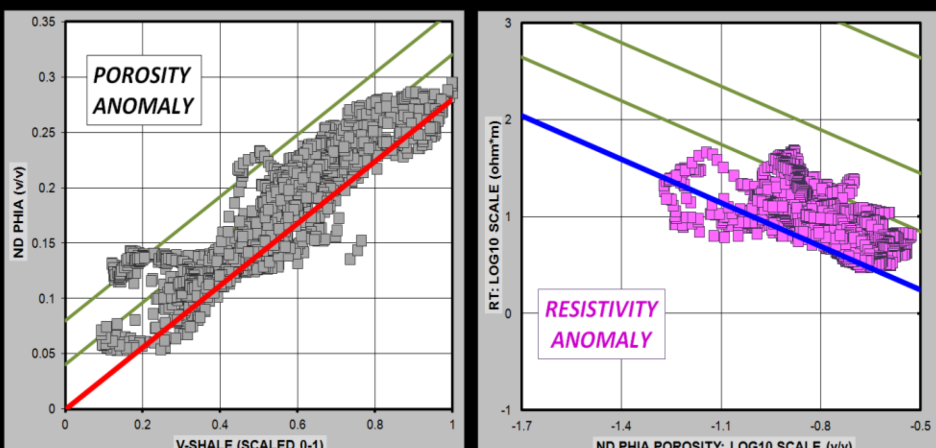
RESISTIVITYITY BASELINE IS BLUE



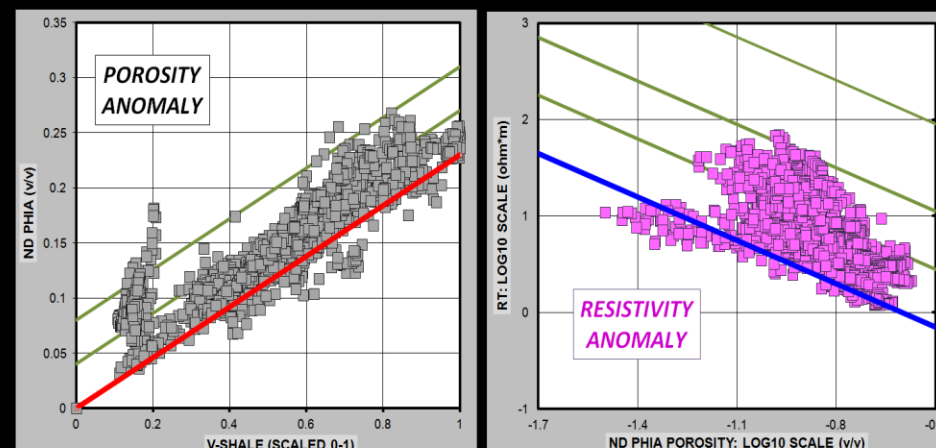
SILO FIELD AREA 49-021-20316-0000



JAKE (HEREFORD) AREA 05-123-13076-0000



WATTENBERG AREA 05-123-29720-0000



NE WELD CO. AREA 05-123-14348-0000

ONCE WE AGREE ON THE BASELINE POSITION,

WE CANNOT DISAGREE ABOUT SUBSEQUENT INTERPRETATIONS

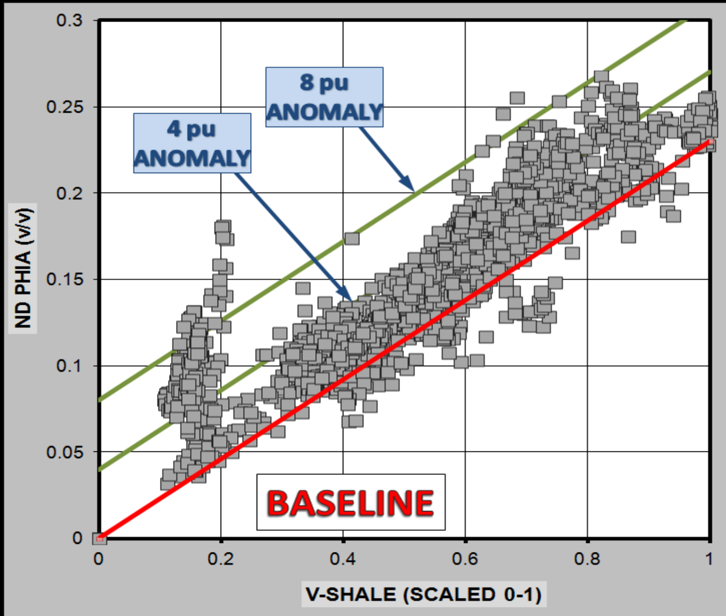
BASELINE / ANOMALY COMPARISONS

- I want to show some other examples of the porosity and resistivity anomaly in the Niobrara section from different areas around the DJ Basin. These areas will be shown on a map later in the presentation. Each cross-plot pair represents data from a single well located in the noted area. The baseline filters are all established by the methods just described using only the internal structure of the data. You see some minor variation in the slopes and intercepts of the trends but basically the baselines look similar and they all look reasonable.
- Now we may disagree about the exact positioning of the baselines for analysis of any well's data, but those differences can be resolved easily. So, an added advantage of this method in an exploration setting…is that once a team has agreed on these baselines, there really is no further disagreement on resulting interpretations.
- *<u>NOTE</u>: The NE Weld Co. well (starred) was used in our detailed examination of the porosity and resistivity baselines and will be used several more times in the presentation as the type example of the log evaluation method to which other data are compared.*

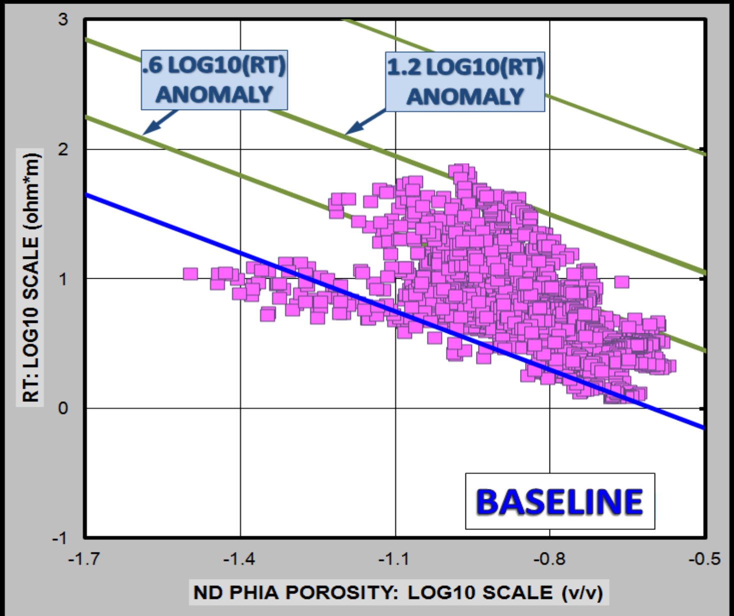
DJ BASIN: NIOBRARA EXAMPLE (LOG)

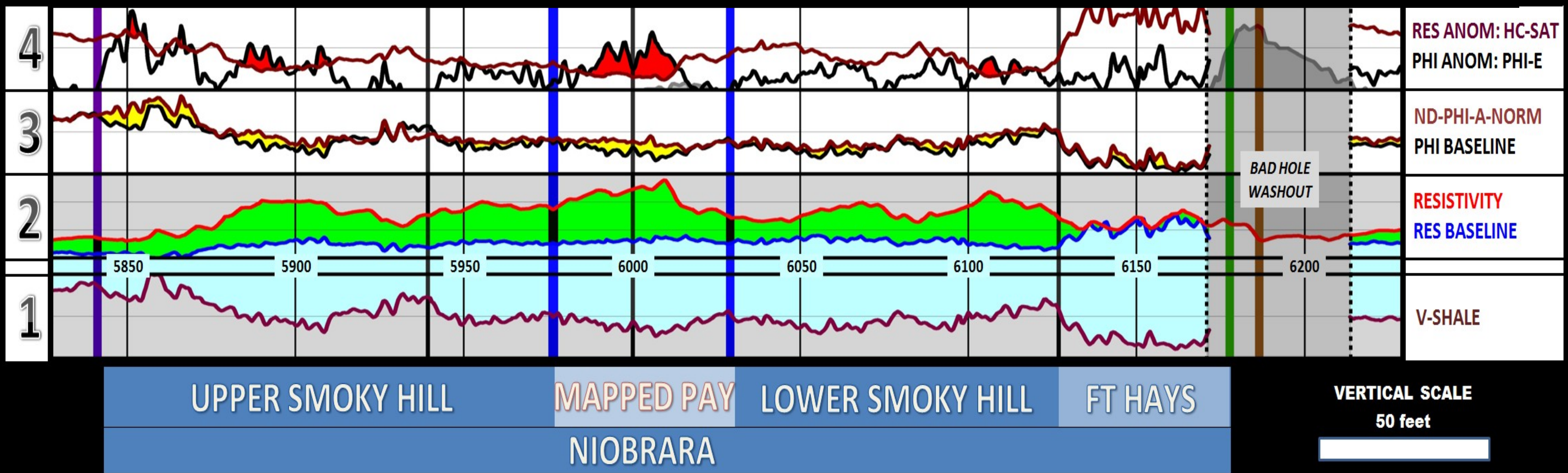
DJ BASIN: NIOBRARA WELL EXAMPLE

POROSITY ANOMALY



RESISTIVITY ANOMALY

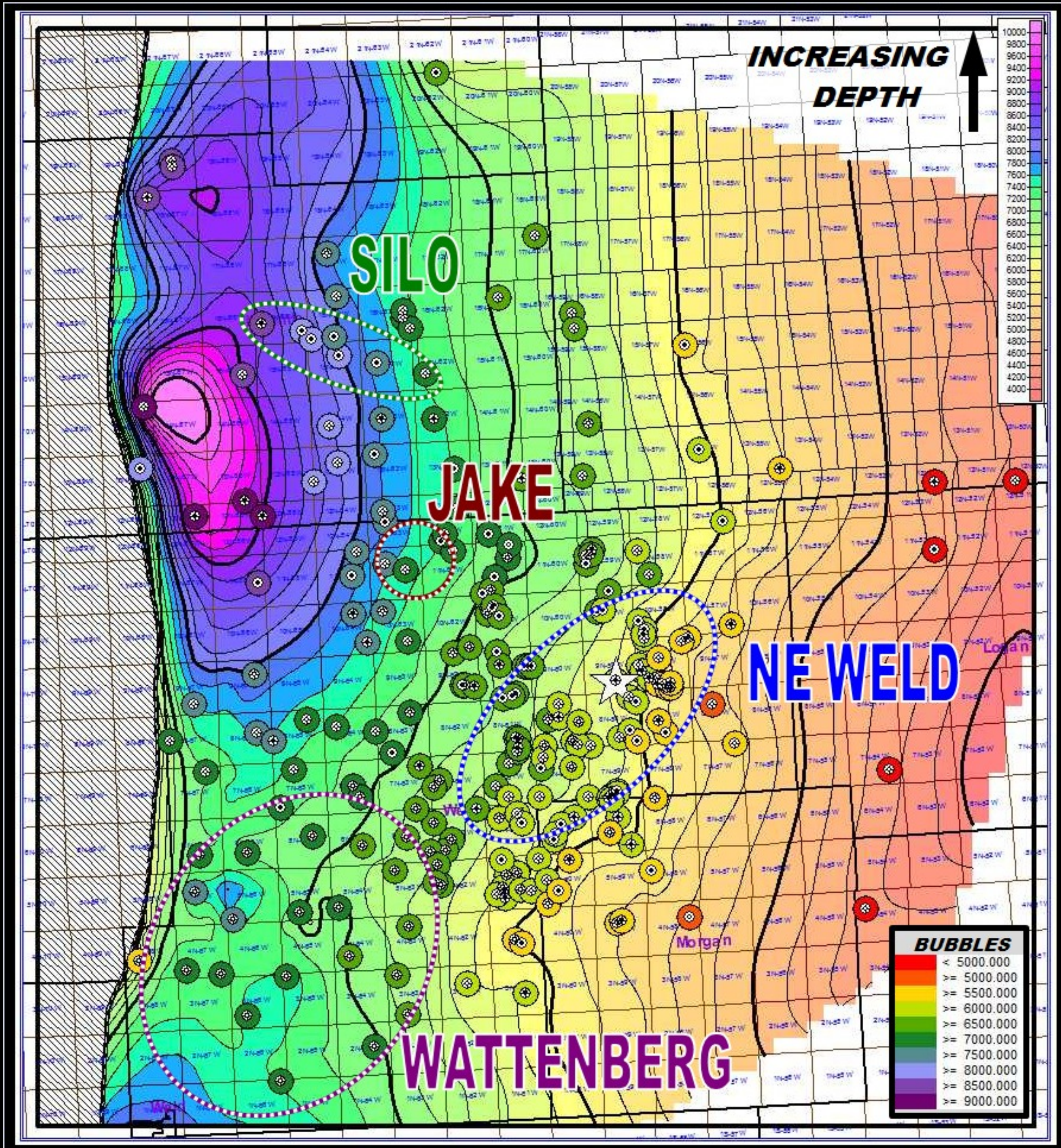




DJ BASIN: NIOBRARA EXAMPLE (LOG)

- I think at this point I owe you a look at these evaluations in a log format, versus depth. On top are the two examples we just looked at in our deep dive and below is a log that presents all these results again in a form you may prefer instead of the cross-plots.
- In Track 1 you see the V-Shale, Track 2 presents Resistivity in red with the Baseline filter in blue – the amount of surprise is shown in green as separation between the two curves and basically defines the extent of the petroleum system. As is typical in mature organically-rich shale plays, hydrocarbon saturation is not the critical issue as shown by the wide separation through the Niobrara interval. Track 3 shows the normalized porosity in brown with the baseline filter in black; the surprise anomaly is shown as the difference between the two curves in yellow. The narrow separation here does identify a critical issue in this play: storage and deliverability from the rock matrix. And finally Track 4 shows the porosity anomaly increasing upward and the resistivity anomaly increasing downward.
- Intervals in which the two anomalies coincide are colored red in Track 4 and indicate sections with the highest probability of having effective porosity that is also HC saturated. These are of course the prospective target intervals.

DJ BASIN: NIOBRARA EXAMPLE (LOCATION)



STRUCTURE: MD TO BASE NIOBRARA

TYPE-WELL LOCATION

REFERENCE AREAS

SILO

JAKE

NE WELD

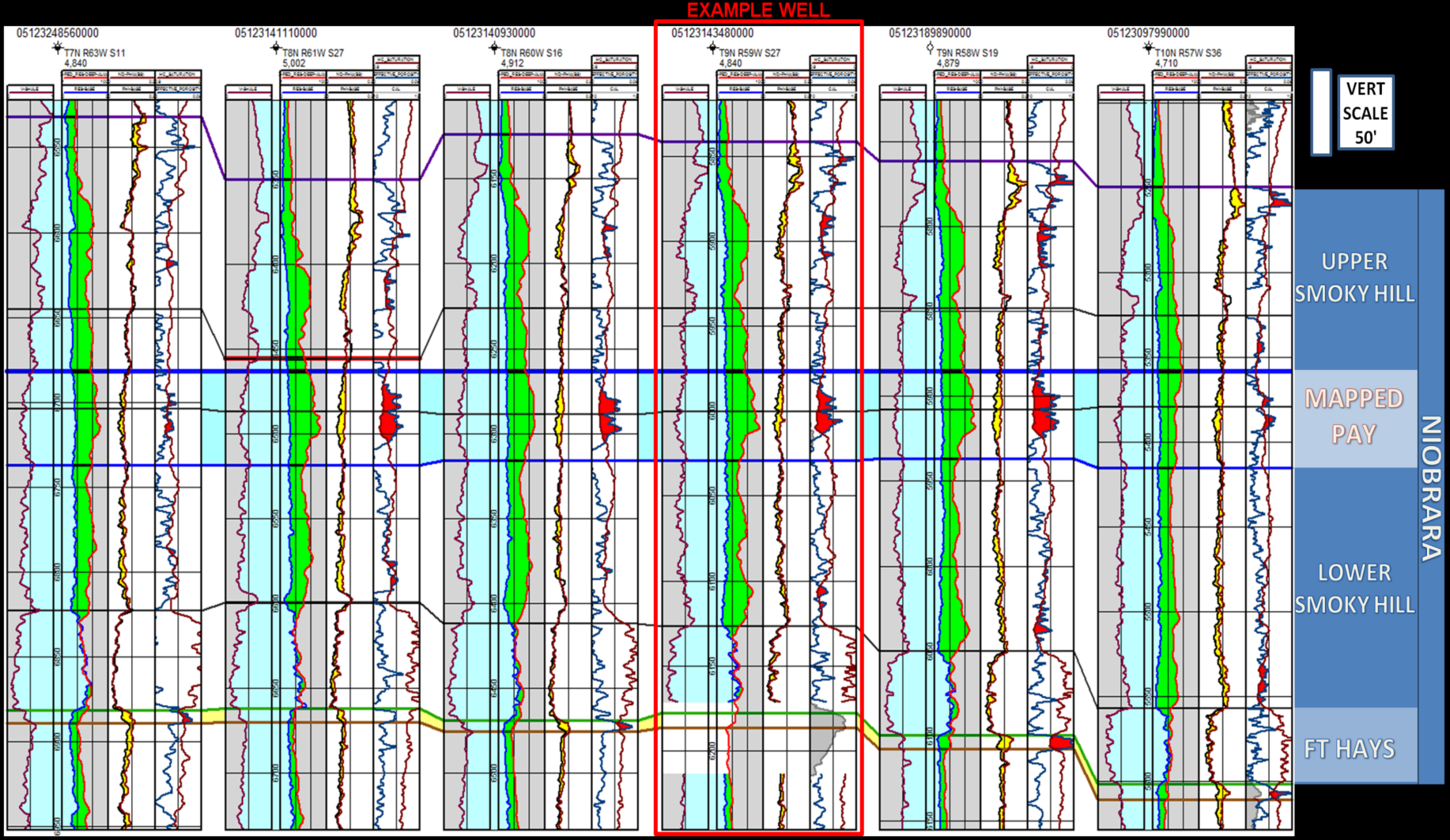
WATTENBERG

n = 226 wells

DJ BASIN: NIOBRARA EXAMPLE (LOCATION)

- We turn to an area of the DJ Basin just NE of Denver. This map shows measured depth to the base of the Niobrara. Colored bubbles show the locations of contoured data. Hot colors in both the grid and bubbles indicate shallower depths. A west-dipping monoclinal flank with two synclinal centers is apparent. The four areas previously mentioned are highlighted for geographic reference. And finally, the location for the previous type log is indicated by a star in the NE Weld County area.
- A cross-section showing continuity of the stratigraphy and log evaluations both updip and downdip of the type well is included in the next slide.

DJ BASIN: NIOBRARA EXAMPLE (PHIE - HCSAT)

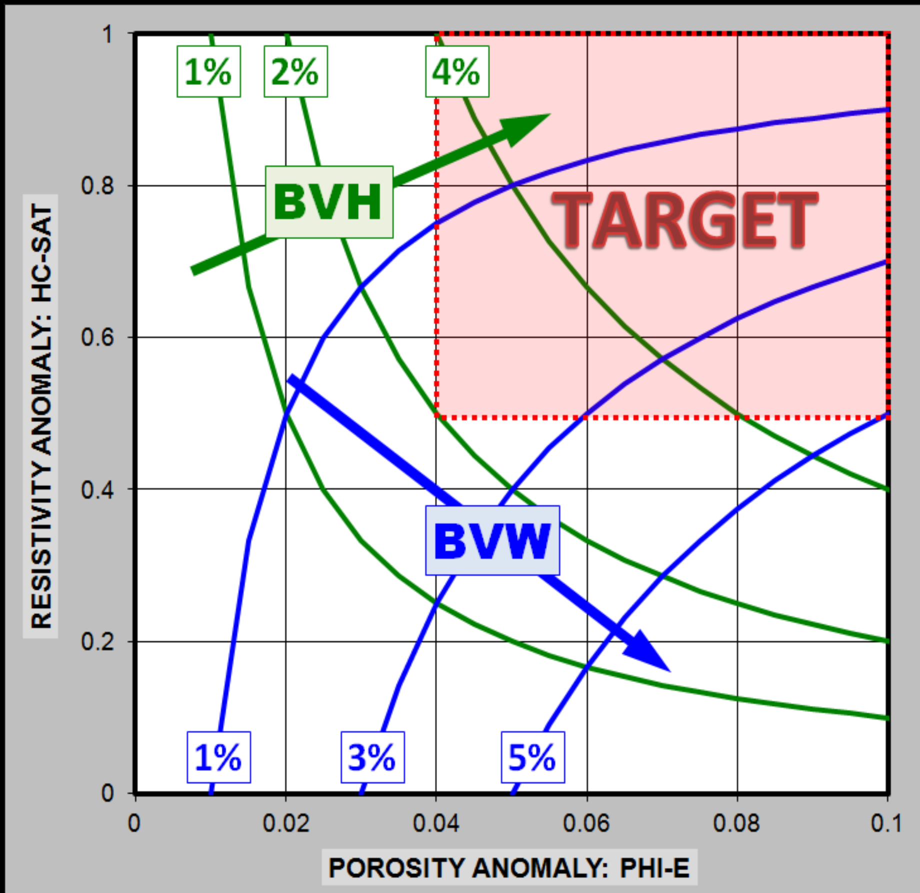


Well	PHIE	HCSAT
05123248560000	.016	.63
05123141110000	.026	.68
05123140930000	.022	.68
05123143480000	.021	.68
05123189890000	.028	.71
05123097990000	.023	.58

DJ BASIN: NIOBRARA EXAMPLE (PHIE - HCSAT)

- This six-well stratigraphic cross-section shows the Niobrara interval from the heart of the map area. By design, the stratigraphic nomenclature is generalized to avoid any confusion based on that topic. The log curves are the same as what was described in the type-well slide. The generally continuous character of the Niobrara petroleum system across this area is fairly obvious based on the ubiquitous resistivity anomaly.
- The average effective porosity and HC saturation interpreted from the anomalies for the identified pay interval are noted below each log. In general, PHIE **decreases** into the basin and HCSAT **increases** into the basin. These are typical characteristics of shale resource plays and…similar to the log display…the most prospective areas start where the best porosity anomaly intersects with the best saturation anomaly. As for most oil resource plays in mature, organic-rich shales, the critical issue doesn't appear to be HC saturation…it's reservoir quality and resource deliverability. The obvious pay interval highlighted here is significant due to the development of a superior porosity anomaly.
- The two parameters, PHIE and HCSAT, represent just the first steps to a process in which these are combined with other data from primary analysis (v-shale and interval thickness) and meta-data evaluation for an increased understanding of reservoir deliverability. Some interesting techniques and results of the meta-analysis are described next.

MESSAGES IN THE DATA STRUCTURE



META-DATA

BVH = PHIE x HCSAT

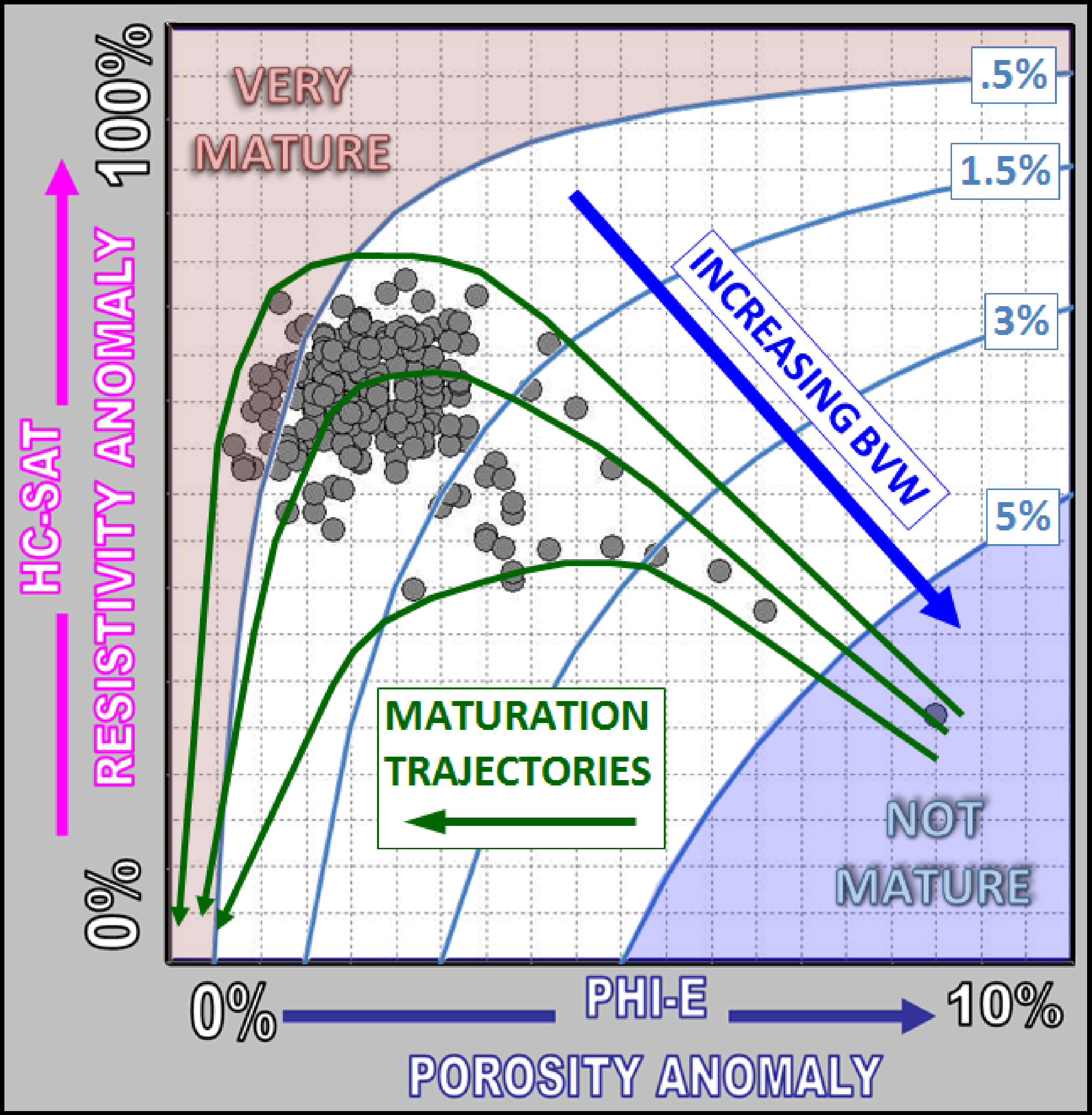
BVW = PHIE x (1-HCSAT)

1) BVW and BURIAL HISTORY
2) PHIE-HCSAT SLOPE and PORE STRUCTURE
3) BVH and PERMEABILITY, FLUID COMPATIBILITY

MESSAGES IN THE DATA STRUCTURE

- In the rest of the presentation, I want to move past the obvious messages of the simple anomalies to a different, higher level, evaluation. These meta-data include bulk-volume hydrocarbon (BVH=PHIE x HCSAT) and bulk-volume water (BVW=PHIE x (1-HCSAT)). The relationships among the primary parameters and the meta-data can be seen in the cross-plot shown here. This plot can be used in log evaluation, to compare data from the ½-foot depth step in a single well; or in mapping, to compare the average properties of a pay interval among a series of wells.
- I am going to review results from three topics shown on the slide which I hope will expose you to interpretations you have never considered before. These include: (1) a look at burial history through bulk-volume water, (2) an evaluation of pore structure with the correlation of PHIE and HCSAT, and (3) using bulk-volume HC for permeability and fluid compatibility evaluation.

BVW and BURIAL MATURITY



n = 226 wells

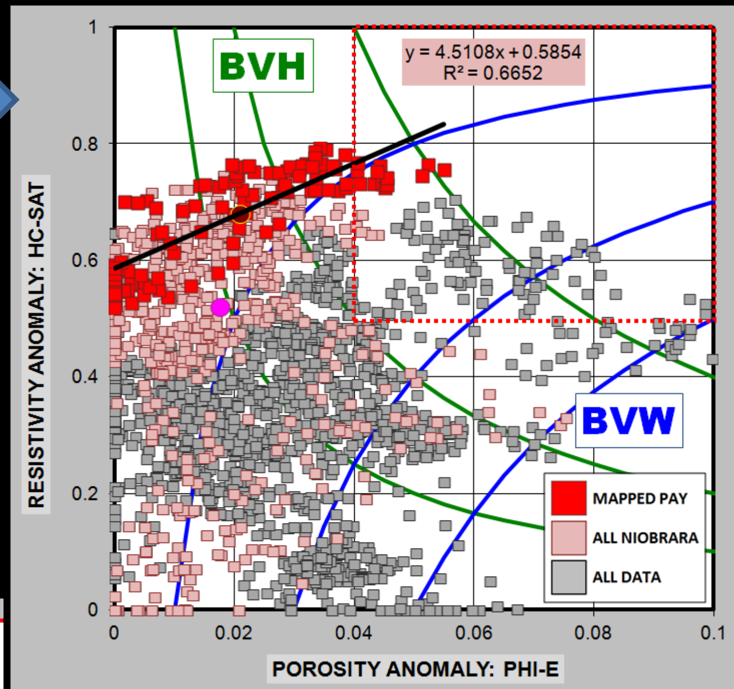
BVW and BURIAL MATURITY

- The only way to make this discussion brief is to baldly state the hypothesis/conclusion first: BVW is the single best metric of burial maturity available from log data, including PHIE, HCSAT, BVH and BVW. BVW is the only parameter that shows an unrelenting, unidirectional reduction during burial history. These concepts are illustrated in the PHIE-HCSAT cross-plot with a series of lines labeled as maturation trajectories. In this plot each point represents the average BVW from a single well calculated for the Niobrara "pay" interval (shown previously in the type log).
- When water is the movable fluid phase, BVW is reduced by water expulsion with porosity loss during compaction coupled with increasing HC generation and higher HC saturation. This phase of the burial history is represented by maturation trajectories sloping upward from the lower right corner of the plot toward the upper left. Peak HC saturation is attained when the reservoir reaches irreducible water saturation (SwIRR) and hydrocarbons become the primary movable fluid phase. Thereafter, porosity reduction continues by compaction; however, the maturation trajectories turn downward toward the lower left corner of the plot as hydrocarbons are preferentially expelled and HC saturation decreases. Here BVW also slowly decreases in response to lower porosity and associated lower SwIRR.
- The end point for a shale taken to deeper burial depths should be a reservoir with (1) zero effective porosity, (2) residual HC saturation and (3) irreducible bound water located somewhere near the origin of the cross-plot. The deepest data for the Niobrara in the DJ Basin have not yet approached these conditions and therefore do not demonstrate these effects. The maturation trajectories beyond the dataset toward the plot origin represent hypothetical projections based on inference from other shale plays in other basins.

PHIE-HCSAT SLOPE and PORE STRUCTURE (1)

B

BASIN FLANK
POSITIVE SLOPE



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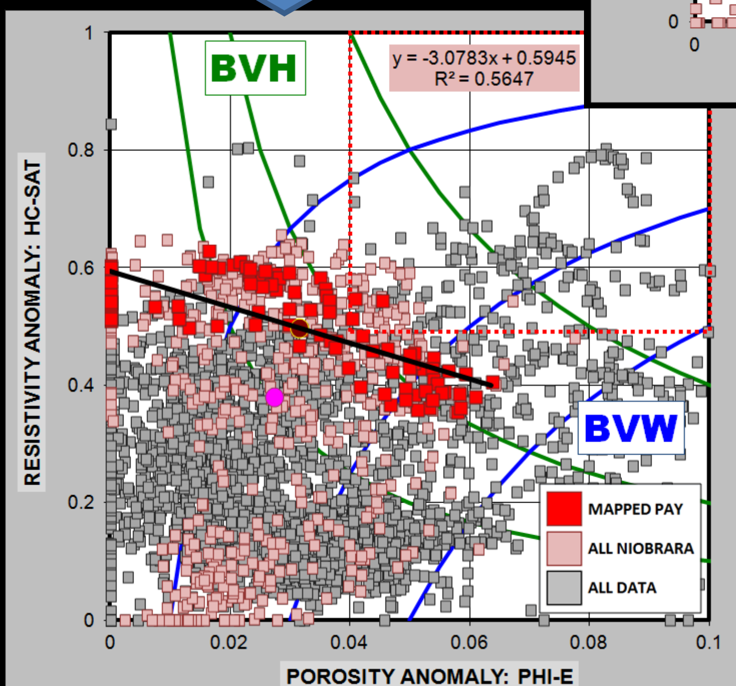
~1500' of data in each plot

C

DOWNDIP
INVERSE
SLOPE

A

UPDIP
INVERSE
SLOPE



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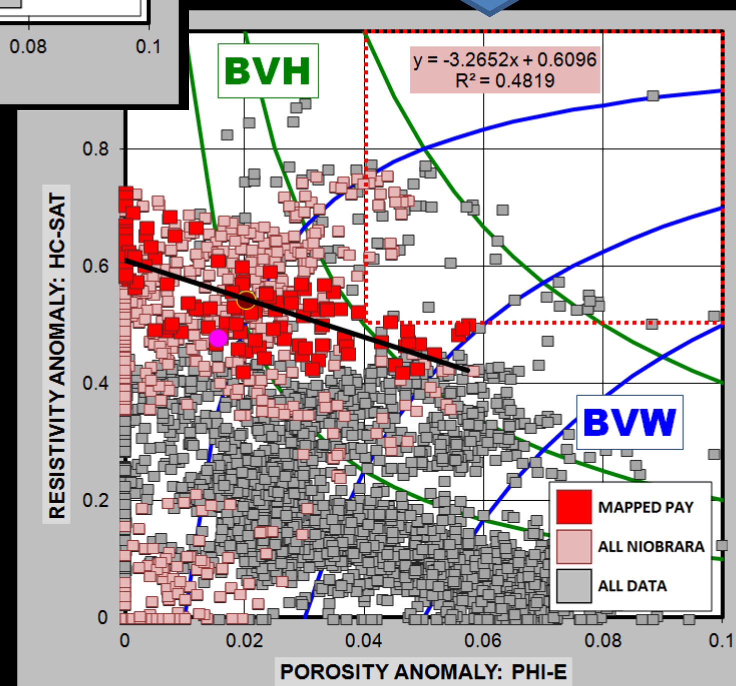

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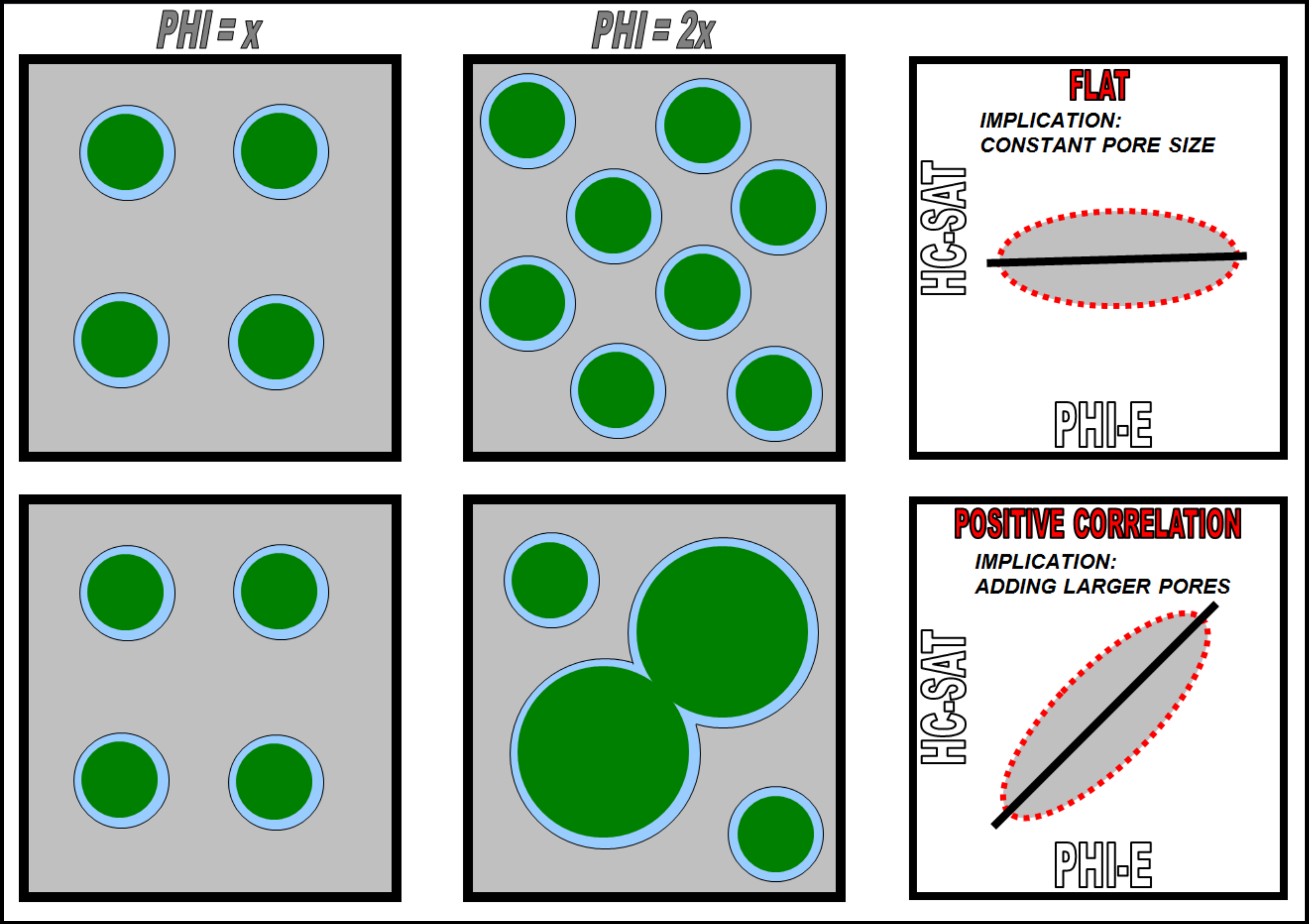
PHIE-HCSAT SLOPE and PORE STRUCTURE (1)

- The next topic requires some observation prior to discussion. We are going to look at log data in three wells from updip to downdip across the NE Weld County area. Each plot shows the PHIE-HCSAT cross-plot for about 1500’ of data from a single well; pay-zone data are red, the rest of the Niobrara date are pink, and all remaining data are gray. A regression trend correlating PHIE versus HCSAT for the pay-zone data is shown with a bold black line; the slope of that trend line is the focus of our attention.
- In the most updip well (A) the slope of the trend is inverse (negative) with higher porosity having lower HC saturation. In a distinct fairway along the middling depths of the basin (B) the slope changes to a positive trend with higher HC saturations associated with better porosity. And then (C) the slope of the trend reverses again (unexpectedly) becoming negative in the downdip, deeper part of the basin.
- So what’s going on here?

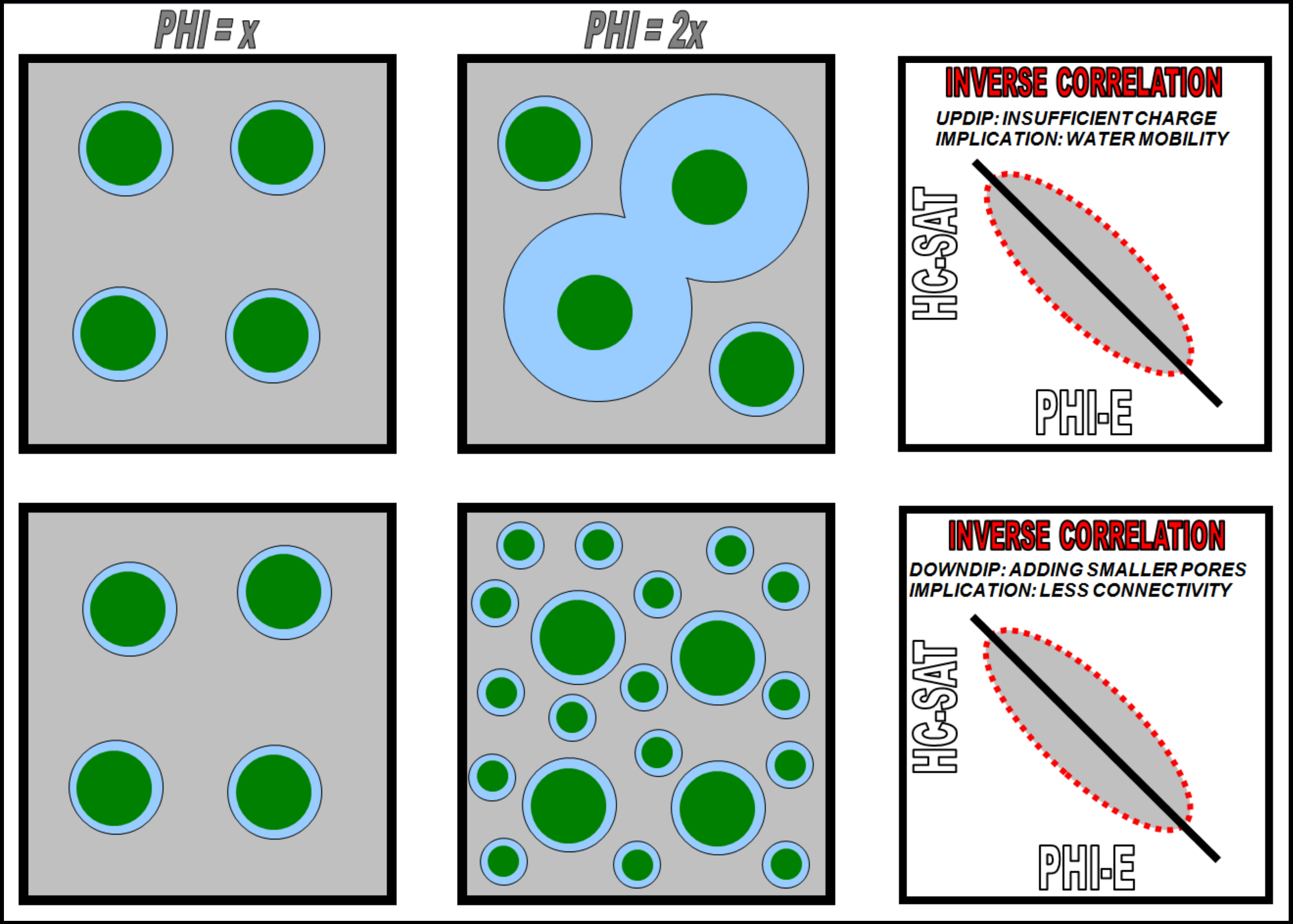
PHIE-HCSAT SLOPE and PORE STRUCTURE (2)



PHIE-HCSAT SLOPE and PORE STRUCTURE (2)

- The character of the data correlations just described is revealing important details about the changing pore structure of the reservoir.
- Consider a rock with (PHI=X) that is saturated with HC to SwIRR. If we double the porosity of the rock (PHI=2X) by adding only pores of a similar size, the PHIE will increase but HCSAT will remain the same (not BVH…just HCSAT). For this case the PHIE-HCSAT correlation will produce a flat line with very low positive or negative slope.
- But, if we double the porosity by adding larger pores (and we have enough HC charge to maintain SwIRR) then the HCSAT of the reservoir will increase as porosity increases. The increased pore volume is produced by addition of pore space with less total surface area and thus lower bound water volume than where pores of the same size are added. This pore structure should imply better connectivity among pores and is signaled by the positive correlation between PHIE and HCSAT.

PHIE-HCSAT SLOPE and PORE STRUCTURE (3)



PHIE-HCSAT SLOPE and PORE STRUCTURE (3)

- Continuing the theme, let's look for explanations of the negative (inverse) slope. Again, if we double the porosity of the rock by adding larger pores but have an insufficient HC charge to maintain SwIRR then the result will be a lower HCSAT and inverse correlation of PHIE and HCSAT with lots of moveable water. This seems like a reasonable (obvious) explanation for the inverse correlation seen in the updip portion of the reservoir where we have previously shown higher BVW.
- But the negative slope seen in downdip wells suggests a more subtle change in pore structure. Here I think we are increasing the pore volume by adding smaller pores. Because the smaller pores carry a proportionally larger bound water volume (more total surface area) the increased porosity is associated with higher Sw and lower HCSAT. The implication of smaller pores signaled by the inverse slopes in downdip areas is less reservoir connectivity and poor fluid deliverability of any kind.
- These results can be confirmed with simple mathematical models using spherical shapes which demonstrate the positive or negative slope depending on the relationship between total pore volume and total surface area (although the correlations are not strictly linear). Based on the previous discussions, it seems reasonable to expect better reservoir performance due to enhanced pore connectivity where the pay zone shows the positive correlation between the porosity and resistivity anomalies.

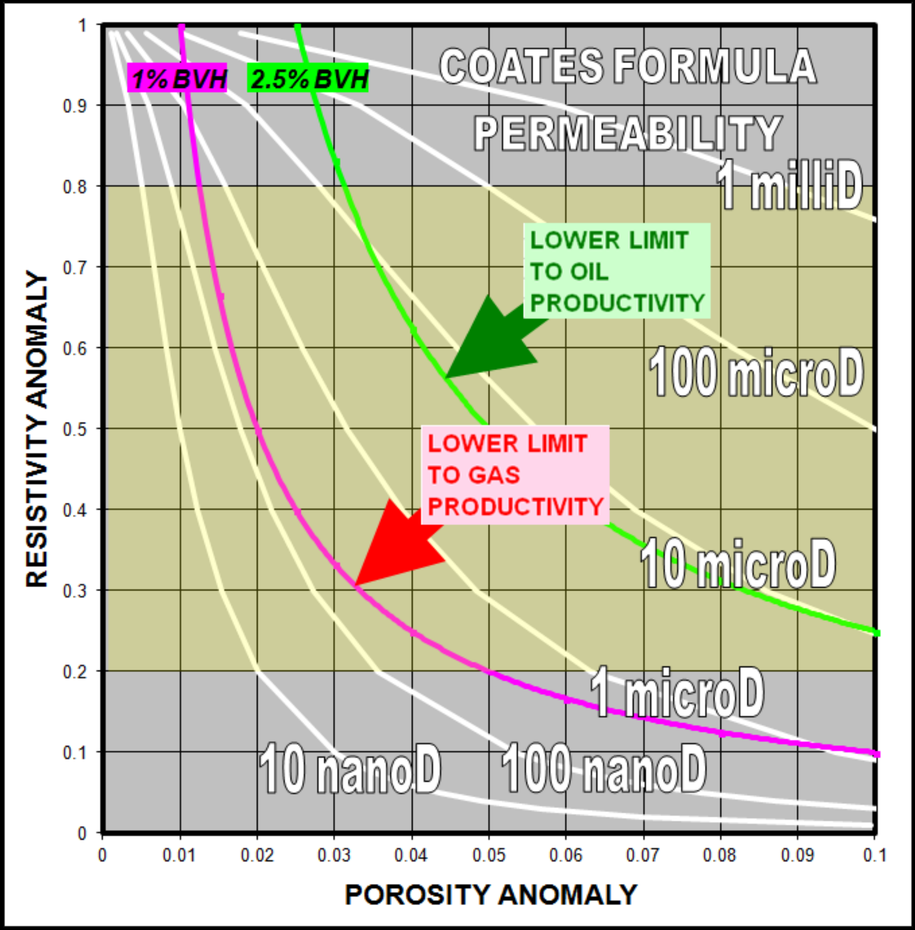
PERMEABILITY and FLUID COMPATIBILITY

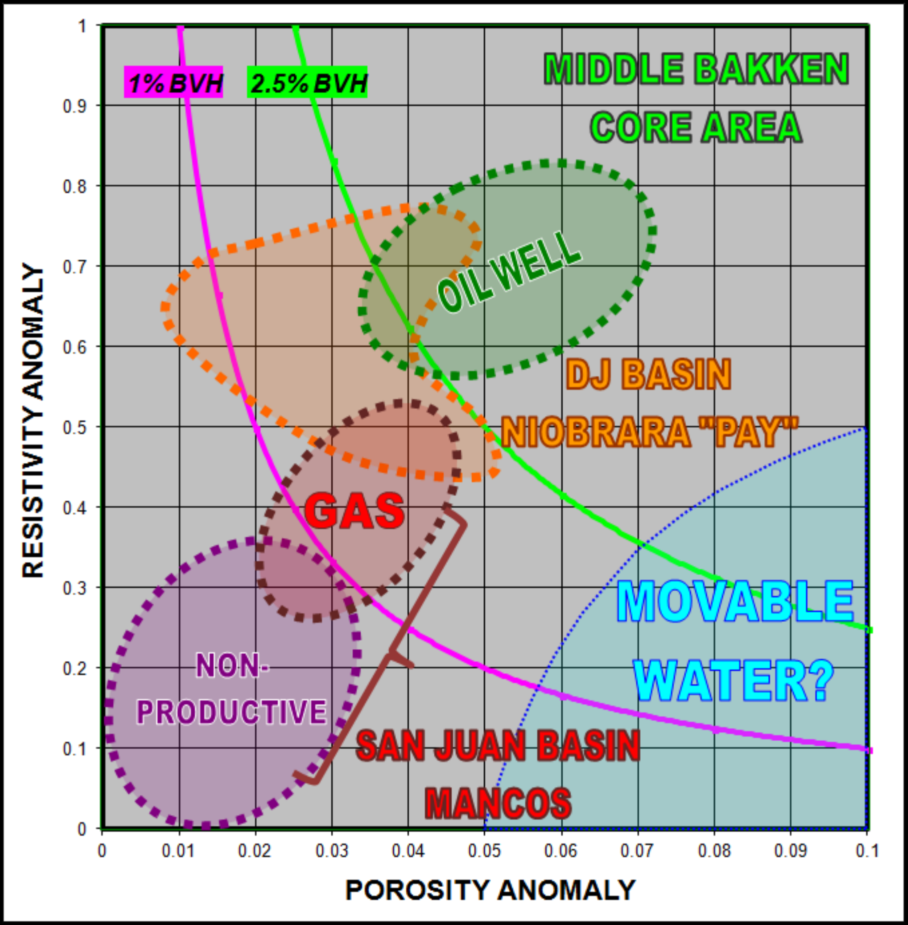
MODIFIED COATES FORMULA FOR PERMEABILITY

$$k = [100 * (PHIE^2) * (HCSAT) / (1-HCSAT)]^2$$

HCSAT ASSUMES Sw=SwIRR

ORIGINAL SOURCE: Log Interpretation Principles/Applications (1989)
Chapter 10: Permeability and Productivity, pages 10-3 to 10-5





PERMEABILITY and FLUID COMPATIBILITY

- My last example uses average BVH from PHIE and HCSAT as a reservoir parameter that is intended to approximate (or at least correlate with) permeability. We can see that this is a reasonable request of the data by looking at the modified Coates formula for permeability at the top of the slide. Only two parameters are used in the calculation: (1) effective porosity, which I have on the x-axis of my meta-data plot and (2) HCSAT, represented on the y-axis of the plot (of course HCSAT=(1-Sw)). We have to accept that all the samples are at SwIRR which is probably mostly true as long as BVW is low (<3-5%).
- Permeability calculated from this Coates model is shown in the plot from the lower left of the slide. Here you can see that the lines of iso-permeability and iso-BVH are generally parallel over a large portion of the diagram (shaded in yellow). This is a reasonable association: for reservoirs with the same effective porosity, a reservoir that can generate a lower SwIRR (higher HCSAT) should have a better distribution of pore throats, and hence, higher permeability. Note that 1% BVH correlates approximately with a permeability of around 200 nanoDarcy and 2.5% BVH correlates approximately with a permeability of around 10 microDarcy (a 50-times change in permeability for a 2.5-times increase in average BVH).
- I have studied these data from a number of plays shown in the plot at the lower right of the slide and I can suggest with some confidence that the 2.5% average BVH (~10 µD) boundary serves as a useful operational lower limit for flow to liquids from an unconventional reservoir. And, owing to the smaller molecular size of methane, the operational lower limit to gas flow appears to occur at the 1.0% average BVH (~200 nD) boundary.
- Areas of successful development can only be expected where the reservoir fluids are compatible with the mapped reservoir potential. In many plays, the greatest probability for economic oil recovery is limited to specific areas (“sweet spots”) where the reservoir has permeability to liquids and a favorable pore structure including better pore connectivity.

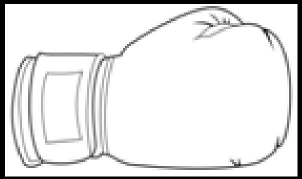
HEAVYWEIGHT BOUT: ROUND 15

GUS ARCHIE:

PETROPHYSICAL THEORY

DETERMINISTIC

BASED ON MEASURED PARAMETERS



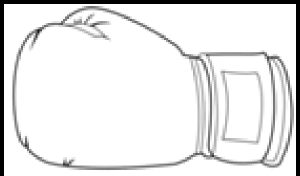
PROBABILISTIC EVALUATION
IS NOT RIGOROUS ENOUGH

CLAUDE SHANNON:

INFORMATION THEORY

PROBABILISTIC

BASED ON DATA STRUCTURE



TOO MUCH UNCERTAINTY IN
DETERMINISTIC PARAMETERS

HEAVYWEIGHT BOUT: ROUND 15

- We have now come to the last round in this heavyweight bout between Gus Archie and Claude Shannon. So who wins: is it petrophysics using a deterministic approach; or the probabilistic methods guided by Information Theory?
- If we look for a weakness in each, I think the petrophysists would say that a probabilistic evaluation is not rigorous enough for what they do. And now counterpunching for Shannon: I think that there may be more uncertainty to the deterministic approach than the experts typically let on.

AND THE WINNER IS…

For exploration…

…deterministic pitfall:

It ain't what you don't know that gets you into trouble.
It's what you know for sure that just ain't so.

--- Charles F. Kettering (V.P. GM Research, 1920-1947)

For exploration…

...a simple process of log analysis based on
Claude Shannon's INFORMATION THEORY:

(1) Is a probabilistic tool for identification of information/signal.
(2) Uses only the internal structure of the data (baseline/anomaly).
(3) Provides effective interpretations for the evaluation of resource potential in unconventional reservoirs *(PHIE-HCSAT)* .

AND THE WINNER IS…

- Of course this is not really an either/or question. But for exploration, the one deterministic pitfall expressed in the quote shown here has been enough to drive me to seek alternative answers.
- I have described for you one probabilistic approach that I find unusually effective. I have shown you three things that make Claude Shannon's Information Theory a useful guide for log evaluation in exploration.
- Further, I have shown that meta-analysis of the basic log evaluation parameters can reveal important insights for interpreting basin-scale variations in reservoir quality and resource deliverability across an exploration play.

THANK YOU
and
ACKNOWLEDGEMENTS

WPX Energy for permission to present these ideas and results.

RMS-AAPG for the opportunity to make the presentation today.

The Audience for your time and attention.

People are very open-minded about new things - as long as they're exactly like the old ones.
(Charles F. Kettering)

THANK YOU
and
ACKNOWLEDGEMENTS

- The emphasis in this talk has obviously been on a new approach to log evaluation without petrophysics. I’m hoping you will leave the presentation thinking: “Well, that was certainly different.” If that’s the case then my effort has been a success.
- I want to thank everyone who helped make this presentation possible.

Appendix (1): PAC Learning

PROBABLY APPROXIMATELY CORRECT

Nature's Algorithms for Learning and Prospering in a Complex World

Leslie Valiant

Basic Books, 2013

Learning includes finding patterns in data that are usefully predictive of future events but do not necessarily provide an explanatory theory

Predictions need not be perfect or even the best possible; they need merely to be useful enough

Computational Methods alone produce algorithms that are as efficient and effective as physical laws

Appendix (1): PAC Learning

- Earlier, I described the idea that, for exploration, I am trying to generate answers that are "probably approximately correct". You might have taken that phrase as an attempt at rhetorical humor; but, in fact, PAC Learning (PAC stands for Probably Approximately Correct) is a recently developed concept from the world of artificial intelligence and machine learning. I think it is striking how well the scientific tenants from this learning framework correspond with the principles of Claude Shannon's Information Theory and provide very effective guidelines for organization of an exploration study.